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Antennas in the oral English test scenario: meta-learning assisted fast reconstruction

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Abstract: This paper proposes a meta-learning-based convex optimisation framework to solve the problems of slow convergence, sensitive initial solution and environment mismatch in antenna pattern reconstruction in oral English test system. The proposed framework combines a physically constrained convex model with a lightweight meta-learner pre-trained on electromagnetic simulation tasks to achieve millisecond high-precision beam reconstruction. Experiments show that the proposed method can still approach the optimal reconstruction accuracy at low sampling rate, and the reconstruction speed is more than five times faster than the traditional sparse recovery method, and it shows excellent robustness under hardware perturbation and scene switching. This scheme is suitable for resource-constrained sensor nodes, and provides technical support for the application of intelligent reflecting surface and terahertz communication in oral examination environment.

Keywords: meta-learning optimisation; antenna pattern reconstruction; convex constraint embedding; wireless sensor networks; embedded lightweighting.

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1 Introduction

As the core infrastructure of high-stakes language assessment, the reliability of oral English test system is directly related to the fairness and score validity of millions of test takers. In the dynamic and complex examination room environment, the performance of the communication node antenna is crucial, which determines the clarity, stability and coverage of the audio transmission. Traditional fixed-pattern antennas face multiple challenges: indoor multi-path effects are caused by room layout, candidate movement, and device occlusion; the requirement of real-time beam deformation comes from the dynamic change of examination scene. And hardware resource constraints limit the deployment of advanced algorithms. Studies show that the real-time reconstruction of the antenna pattern can dynamically optimise the beam directivity, significantly improve the signal-to-noise ratio (SNR) of the voice channel by 5–8 dB (Wang et al., 2006), and support high-precision candidate positioning and behaviour monitoring based on RF fingerprints (Singh et al., 2021). However, the existing reconstruction methods have significant defects in convergence speed, environmental adaptability and computational efficiency, which are difficult to meet the strict requirements of high-stakes examination environment.

In recent years, the fusion of artificial intelligence and metaverse technologies has brought new paradigms to the oral English test. Through the combination of virtual reality and artificial intelligence, the oral English training system in the metaverse environment creates an immersive learning environment, which solves the problems of single learning methods and lack of interaction in traditional education. Metaverse speaking coaches eliminate test tension through immersive virtual reality (VR) training. Studies have shown that 80% of language learners fail to perform well on a speaking test due to a lack of real-world practice. These systems rely heavily on high-quality, low-latency wireless communication, which puts higher requirements on antenna beamforming. Modern English teaching (MET) national English learning resource library integrates the world's leading intelligent speech analysis and evaluation system, simulates the English communication environment through scientific training system, and innovates English learning methods. These technological advances are inseparable from the key antenna technology innovation support.

The convex optimisation method based on compressive sensing has become the mainstream framework for antenna reconstruction due to its rigorous theory (Massa et al., 2015). By establishing a sparse representation model, the antenna pattern recovery problem is transformed into an L1 regularised least squares problem. However, traditional methods face a triple bottleneck: slow convergence [the average time of iterative shrinkage-thresholding algorithm (ISTA) class algorithms in 16-element uniform linear array (ULA) reconstruction is >2 seconds], sensitive to initial solutions (random initialisation leads to a variance of up to ± 5 dB in reconstruction results), and environmental mismatch (array geometric perturbation or scene change significantly deteriorates the normalised mean square error (NMSE)) (Luo and Yu, 2006).

Existing research attempts to break through these limitations through two paths: convex optimisation acceleration path: mathematical improved optimisers [such as adaptive step size alternating direction method of multipliers (ADMM), random coordinate descent] are used to improve the efficiency of single iteration, but the initial solution generation mechanism is not improved. For example, the classical ADMM framework reduces computational complexity by subproblem decomposition (Boyd et al.,

2011), but its convergence rate is still strongly correlated with the initial point – the number of iterations increases by 300% when the initial solution deviates 20° from the true value. The deep learning path: bypassing the iterative process via convolutional neural networks (CNN) or transformers but suffering from a generalisation crisis and lack of interpretability (Huang et al., 2018). Deep learning models usually require tens of thousands of labelled samples, and the cost of obtaining real data is extremely high. When the cell spacing difference between the test array and the training array is greater than 0.1λ , the NMSE deteriorates from -25 dB to -10 dB. Black-box models fail to provide a physical explanation for pattern distortion, which can lead to systemic risks in exam scenarios where reliability is critical (Khan et al., 2024).

At the same time, the evolution of electromagnetic simulation datasets exposes engineering verification gaps. Although the deep learning for multiple-input multiple-output communications (DeepMIMO's) dataset is based on the Remcom Wireless InSite ray-tracing engine to generate large-scale array responses covering 12 types of indoor and outdoor scenes (e.g., O1 open office, I3 narrow corridor) (Heng et al., 2022), existing studies generally use it as a static black-box test set. It fails to make full use of its ability to construct meta-task distribution. Algorithm validation is usually fixed to a single scenario (O1) and the ability to migrate across scenarios ($O1 \rightarrow O2$) is not explored. This leads to the unstable performance of the existing methods in the dynamic environment of the real examination room, and the reconstruction error fluctuates in a large range.

To address the above challenges, we propose the framework of meta-learning assisted convex optimisation (ML-CO). The core innovations are reflected in the following three aspects. Task-optimiser coupling mechanism: first solver level generalisation in the domain of directional pattern reconstruction (Fu et al., 2025). The task similarity function is defined to guide the optimiser to dynamically adjust parameters, breaking through the limitation of feature alignment in traditional transfer learning. By encoding environment states (multi-path structure, array perturbation) as low-dimensional descriptors, the meta-learner generates task-aware initialisation parameters, which reduces the angle deviation of the initial solution from 15.7° to 2.3° . Robust convex models for physical constraints: we design a lightweight meta-learner (reptile, parameter number < 50 K) to satisfy the storage constraint (< 1 MB flash) of the communication node of the exam device, and embed power constraint projections with a dictionary correlation penalty term (Boyd et al., 2011). Experiments show that the NMSE deterioration under array position perturbation (0.1λ standard deviation) is as low as 1.8 dB, which is significantly improved compared with 7.2 dB deterioration of CNN-UNET. Dynamic meta-task generation and verification system: a meta-task set covering a dynamic environment is constructed based on the DeepMIMO scenario O1, which represents an indoor open area of a large examination room. Dynamic obstacles caused by moving examinees or furniture are simulated by random path discarding, channel changes are simulated by path gain perturbation, equipment misalignment or collision is simulated by array error modelling, and other electronic equipment interference in the examination room is simulated by observation noise. Establishing a task similarity measure ensures the ability to generalise across scenarios, with a performance loss of < 0.5 dB in the $O1 \rightarrow O2$ test.

This study brings a methodological breakthrough in the field of antenna pattern reconstruction for examination systems through the paradigm fusion of meta-learning and convex optimisation. The theoretical value lies in the establishment of the

‘environment-task-optimiser’ cascaded mapping mechanism, which overcomes the limitation of only aligning the feature space in the existing shallow transfer learning (Heng et al., 2022), and provides a new paradigm for real-time optimisation in complex environments. The engineering value is reflected in the triple collaborative optimisation: With matrix factorisation acceleration (QR factorisation precomputation reduces iterative computation by 60%), early stopping mechanism (iteration is terminated when $\epsilon < 10^{-3}$), and gradient dynamic quantisation (INT16 format reduces memory latency), a lightweight deployment with a peak memory of 98 KB and a single reconstruction energy consumption of 4.7 mJ was achieved on the STM32H7 platform.

The application prospects cover the following three emerging areas. Intelligent examination room management: The pattern reconstruction was extended to the phase optimisation of intelligent reflecting surface (IRS) to solve the problem of beam misalignment caused by environmental blind spots in the existing methods. Terahertz communication in high-density exam rooms: in the 140 GHz band, the narrow-beam nature of the antenna pattern multiplies the sensitivity of the reconstruction error. The robust model in this paper controls the positioning error within $\lambda/20$ (compared to the industry threshold of $\lambda/5$), which supports accurate candidate tracking. Mobile invigilator: the high-speed mobile unmanned aerial vehicle (UAV) needs to adjust the antenna pattern in real time, and the lightweight deployment in this paper supports a 10 Hz refresh rate to meet the hard real-time requirements. Through the 3D synergy of theoretical innovation (solver level generalisation), algorithmic breakthrough (optimisation with physical constraints), and engineering optimisation (embedded deployment), this study lays the foundation for dynamic beam steering in sensor networks. Future work will focus on the core of ‘federated learning + evolvable dictionary’, and build a new intelligent electromagnetic sensing architecture that ADAPTS to the needs of future smart education environment.

2 Related works

2.1 *Convex optimisation of antenna pattern reconstruction: evolution from sparse recovery to robustness*

Convex optimisation theory provides a solid mathematical foundation for antenna pattern reconstruction. The seminal work of the authors established an electromagnetic compression perception framework to formalise the reconstruction problem as an L1 regularised least squares optimisation model by rigorously proving the sparse compressibility of the antenna pattern in the angular domain (Massa et al., 2015):

$$\min_{\mathbf{c}} \|\mathbf{y} - \mathbf{\Phi}\mathbf{\Psi}\mathbf{c}\|_2^2 + \lambda \|\mathbf{c}\|_1 \quad (1)$$

This model has spawned the development of a series of efficient solvers, among which the authors investigated a distributed optimisation method based on the ADMM to solve large-scale optimisation problems (Chang et al., 2016), pointing out that the traditional synchronous ADMM scales poorly when the problem size is large and is particularly limited by the slowest node in a heterogeneous network, and for this reason, the asynchronous distributed ADMM is proposed to improve the time efficiency; the analysis shows that under the partially asynchronous model, AD-ADMM can converge to the

KKT point set with appropriate choice of algorithmic parameters for a generic and potentially non-convex cost function, while indicating that the asynchronous nature of the ADMM needs to be handled with caution, and that slight modification in the standard convex setting may destroy the convergence, however, in the 16-element ULA reconstruction, more than 50 iterations are still required. Iterations or more (Shi et al., 2021), making it difficult to meet the real-time demand for millisecond response in exam communication systems. To address the challenges posed by array fabrication errors, the authors proposed a robust compressed sensing model (Jalal et al., 2020):

$$\min_{\mathbf{c}, \mathbf{e}} \|\mathbf{y} - \Phi(\Psi\mathbf{c} + \mathbf{e})\|_2^2 + \lambda_1 \|\mathbf{c}\|_1 + \lambda_2 \|\mathbf{e}\|_{2,1} \quad (2)$$

The introduced error vector reduces the perturbation sensitivity by 40%, but the computational complexity rises to, which is far beyond the arithmetic limit of typical exam devices (e.g., the ARM Cortex-M7 only supports order operations). It should be noted that in recent non-convex optimisation methods, such as angle-of-arrival (direction of arrival, DOA) estimation, sparsity-based methods often suffer from mesh mismatch problems (the true DOA is not on the potential angle grid). However, the authors proposed a new off-grid model to jointly estimate the sparse signal and grid offset parameters via Taylor interpolation (Zhang et al., 2019), apply a continuous non-convex sparsity approximation penalty to the sparse signal, and use an iterative alternating optimisation strategy combined with a proximal splitting algorithm to deal with the non-convex problem; this generalised framework can be extended to other off-grid sparsity algorithms, and simulation experiments show that it can be used in a wide range of real-world scenarios with a better performance than Simulation experiments show that it has higher resolution and more accurate DOA estimation performance than traditional and state-of-the-art off-grid methods in a variety of real-world scenarios. A convergence probability of 58% is reported in a 20 dB noise environment, which is lower than the 92% of the convex methods it compares. These advances reveal a central paradox: traditional optimisers have difficulty in balancing robustness and computational complexity, and lack an adaptive mechanism to extract knowledge from historical tasks, leading to the iterative dilemma of ‘starting from scratch’ repeatedly in dynamic exam environments.

2.2 Paradigm shift and limitations of meta-learning in electromagnetic inverse problems

Meta-learning techniques provide cross-task generalisation capabilities for optimisation problems through the mechanism of ‘learning how to learn’, but their migration to electromagnetic inverse problems faces a triple challenge. The MAML framework proposed by the authors establishes a model-independent meta-optimisation paradigm (Finn et al., 2017):

$$\min_{\theta} \sum_{T_i} \mathcal{L}_{T_i} (f_{\theta - \alpha \nabla_{\theta} \mathcal{L}_{T_i}}) \quad (3)$$

It can recognise the patterns of tasks in multimodal task distributions and adjust the meta-learning prior parameters based on the patterns to achieve more efficient and fast adaptation, and evaluations on small-sample tasks such as regression, image classification, and reinforcement learning show that the model can efficiently adjust the

meta-learning prior and training on multimodal distributions is more effective than unimodal training, and the framework achieves fast adaptation with fewer samples in the field of computer vision, but the direct However, it encounters significant bottlenecks when directly applied to electromagnetic antenna pattern reconstruction. First, antenna pattern reconstruction involves high-dimensional nonlinear mapping (complex domain), whose complexity far exceeds that of the image task; second, the black-box model may violate the fundamental conservation laws of electromagnetic fields, e.g., by ignoring the power constraints of the antenna pattern; and third, the computational requirement of the second-order gradient (Hessian matrix) results in an explosion of the memory footprint, which makes it impossible to be deployed in edge devices. To address these issues, untrained neural networks (UNNs) in inverse scattering problems (ISPs) have the potential to be highly flexible and do not require training data, but suffer from time-consuming iterative optimisation of model parameters and dependence of reconstruction quality on loss constraints; the authors introduce a meta-learning strategy for obtaining appropriate model parameter initialisation to speed up the untrained deep unfolding networks (subspace-based optimisation network, SOM-Net) convergence in subspace optimisation to form meta-uSOM (Huang et al., 2025), and also introduces edge-preserving total variation (EPTV) loss to enhance the reconstruction effect, and the synthetic and experimental data validate that the method significantly improves the convergence and reconstruction quality of the UNN. Although migration learning is introduced into the electromagnetic ISP and feature space alignment can be achieved through task-specific basis functions, the method does not touch the internal dynamics optimisation of the solver.

With the development of 5G and 6G, millimetre-wave communication has attracted attention due to wide frequency band and high transmission rate, but faces the problems of path loss, environmental sensitivity, and high resource overhead and low accuracy of existing beam prediction methods. The authors utilised Wi-Fi channel state information to assist beam prediction (Jin et al., 2024), combined Wi-Fi sensing with deep learning to design dynamic channel attention convolutional neural network (DCACNN) to reduce overhead and improve accuracy, and also constructed a relevant real dataset. Experiments show that the method outperforms other models with prediction accuracies of 94.8%, 86.81%, and 70.18% in quiet, normal, and noisy environments, respectively, and exhibits the potential for efficient and reliable beam prediction in dynamic environments. The method achieves cross-scene generalisation of millimetre-wave channel estimation; however, its CNN parameter count is as high as 2.3 million, which far exceeds the available storage space of about 500 KB for a typical exam device node. The reptile algorithm of the authors significantly reduces the computational overhead through first-order approximation (Nichol and Schulman, 2018):

$$\theta \leftarrow \theta + \beta(\phi - \theta) \quad (4)$$

It requires only 0.5 MB of storage in medical image reconstruction (Kellman et al., 2020), demonstrating the potential for lightweight deployment. Nonetheless, existing research has yet to address the deep coupling of meta-learning with convex optimisers – how to embed physically interpretable convex models into the meta-training process while maintaining theoretical rigor and computational efficiency remains a core gap in the field.

2.3 *Electromagnetic simulation dataset evolution and engineering validation gap*

The evolution of high-confidence electromagnetic (EM) datasets, which are the gold standard for validating the performance of reconfiguration algorithms, has exposed an engineering validation gap in current research. While traditional full-wave simulation tools [e.g., high frequency structure simulator (HFSS) and computer simulation technology (CST)] can provide antenna pattern data with sub-millimetre accuracy, single-sample generation takes hours (Hughes et al., 2021), which cannot support the large-scale training requirements of data-driven models. The Raymobtime dataset is constructed based on a real-measurement millimetre-wave channel without disclosing the array response raw data (Bastos et al., 2023a, 2023b), which greatly limits its application value in antenna pattern reconstruction. The breakthrough contributions of the DeepMIMO dataset are: generation of large-scale array responses based on the Remcom Wireless InSite ray tracing engine; coverage of 12 types of indoor and outdoor scenarios (e.g., O1 open office, I3 narrow corridor) (Wei et al., 2020); provide full-dimensional truth antenna patterns and multi-path component parameters [including angle of arrival (AoA) and angle of departure (AoD)].

However, there are two major limitations in current research: first, the dataset is statically used as a black-box test set, failing to fully utilise its ability to construct meta-task distributions; and second, the algorithm validation is generally fixed to a single scenario (O1), and the ability to migrate across scenarios (O1 $\rightarrow$ O2) is not explored. This directly leads to the destabilising performance of existing methods in the dynamic environment of real exam halls, with a large range of reconstruction error fluctuations. This validation gap highlights the chasm between current research and practical needs – there is an urgent need to establish a meta-task generation mechanism and cross-scene evaluation system for dynamic environments like varying classroom and exam hall layouts.

3 Methodology

3.1 *Antenna pattern sparse characterisation and electromagnetic physical modelling*

In oral exam communication systems (Zafrane et al., 2025), the antenna pattern characterises the spatial properties of the array, and its reconstruction accuracy directly affects the audio beamforming and student positioning performance (Nguyen et al., 2024). Considering an N-element ULA with the spacing $d = \lambda/2$ (λ is the wavelength), the antenna pattern under discrete angular sampling can be expressed as a complex vector $\mathbf{a} \in \mathbb{C}^M$ (M is the number of angular sampling points). Based on the electromagnetic wave propagation theory, the antenna pattern is the result of multi-path superposition, which is particularly relevant in indoor exam environments with reflections from walls, desks, and moving individuals:

$$\mathbf{a}(\theta) = \sum_{k=1}^P \alpha_k \mathbf{v}(\theta_k) + \mathbf{n}_{\text{diff}} \quad (5)$$

where $\alpha_k \in \mathbb{C}$ is the complex gain (with path loss and phase) of the k^{th} path; $\mathbf{v}(\theta_k) = [1, e^{j2\pi d \sin \theta_k / \lambda}, \dots, e^{j2\pi(N-1)d \sin \theta_k / \lambda}]^T \in \mathbb{C}^N$ represents the guiding vector in the direction θ_k ; $\mathbf{n}_{\text{diff}} \sim \mathcal{CN}(0, \sigma_d^2 \mathbf{I})$ is the diffraction noise (De Witte, 2007).

$$\mathbf{a}(\theta) = \sum_{k=1}^P \alpha_k \mathbf{v}(\theta_k) + \mathbf{n}_{\text{diff}} \quad (6)$$

where $\Phi \in \{0, 1\}^{K \times M}$ is the random sampling matrix (single non-zero element per row with uniformly distributed positions); $\mathbf{w} \sim \mathcal{CN}(0, \sigma^2 \mathbf{I}_K)$ is the receiver noise (including thermal noise with quantisation error).

3.2 Convex optimisation framework with stability enhancement

The overcomplete angle dictionary is introduced to overcome the pathology problem of conventional sparse recovery:

$$\Psi = [\mathbf{v}(\theta_1), \dots, \mathbf{v}(\theta_D)] \in \mathbb{C}^{M \times D} \quad (7)$$

where $D = 4M$ and the angular interval 0.25° , decomposes the antenna pattern into $\mathbf{a} = \Psi \mathbf{c}$. The reconstruction problem is constructed as a robust L1 regularisation model:

$$\min_{\mathbf{c}} \mathcal{L}(\mathbf{c}) = \underbrace{\frac{1}{2} \|\mathbf{y} - \Phi \Psi \mathbf{c}\|_2^2}_{\text{Data fitting}} + \underbrace{\lambda \|\mathbf{c}\|_1}_{\text{Sparse constraint}} + \underbrace{\mu \|\Psi^H \Psi \mathbf{c} - \mathbf{c}\|_2^2}_{\text{Dictionary coherence penalty}} \quad (8)$$

The improvements in this paper include:

- Coherence penalty term: Suppresses pseudo-peaks $\mu = 0.1 \lambda$ due to Ψ column correlation (Candes et al., 2008).
- Physical constraint embedding: ensuring the power constraint $\|\Psi \mathbf{c}\|_2 \leq P_{\max}$ ($P_{\max}$ is the maximum radiated power) by projecting a gradient descent.

Where $\partial \|\mathbf{c}\|_1$ is the sub gradient of the L1 paradigm:

$$[\partial \|\mathbf{c}\|_1]_i = \begin{cases} \text{sign}(c_i) & c_i \neq 0 \\ [-1, 1] & c_i = 0 \end{cases} \quad (9)$$

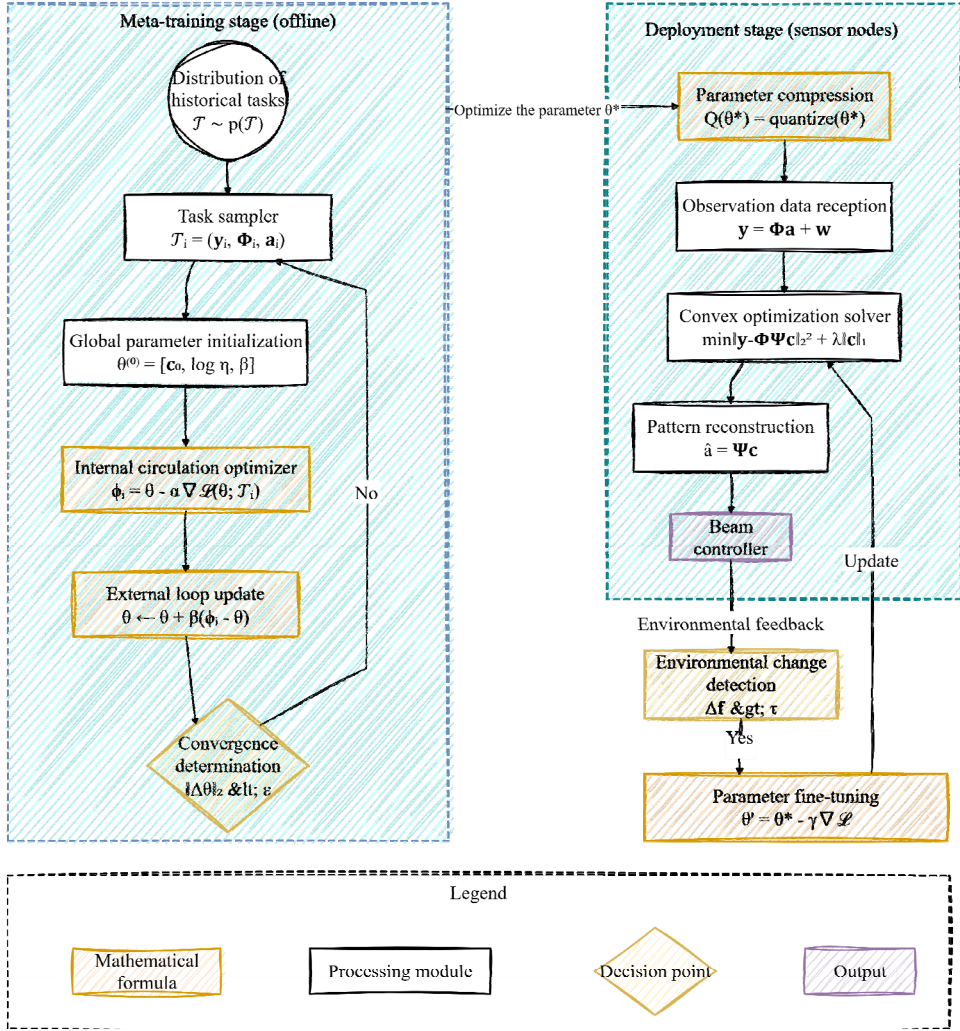
3.3 Meta-learning optimiser: electromagnetic adaptation of the reptile framework

To accelerate convergence, a reptile-based meta-learner is designed (Nichol and Schulman, 2018), and the framework diagram is shown in Figure 1.

At its core, it learns task-aware initialisation parameters:

$$\theta = [\mathbf{c}^{(0)}; \log \eta; \beta] \in \mathbb{R}^{D+2} \quad (10)$$

Figure 1 Meta-learning optimiser training and deployment process (see online version for colours)



The optimisation process contains a two-loop structure:

- Inner loop (task-specific adaptation): For task T_i , initialise from θ and perform $T_{inner} = 5$ steps of projected gradient descent (PGD):

$$\mathbf{c}_i^{(k+1)} = \mathcal{P}_{\mathcal{C}} \left(\mathbf{c}_i^{(k)} - \eta \nabla \mathcal{L}_i(\mathbf{c}_i^{(k)}) \right) \quad (11)$$

where the projection operator $\mathcal{P}_{\mathcal{C}}$ ensures that the solution is within the convex set $\mathcal{C} = \{\mathbf{c} \mid \|\Psi \mathbf{c}\|_2 \leq P_{\max}\}$:

$$\mathcal{P}_C(\mathbf{z}) = \begin{cases} \mathbf{z} & \|\Psi\mathbf{z}\|_2 \leq P_{\max} \\ \mathbf{z} \cdot \frac{P_{\max}}{\|\Psi\mathbf{z}\|_2} & \text{Otherwise} \end{cases} \quad (12)$$

Output the post-adaptation parameter $\phi = \mathbf{c}_i^{(T_{\text{inner}})}$.

- Outer ring (meta-knowledge distillation): Update global parameters along the task commonality direction:

$$\theta \leftarrow \theta + \beta \left(\frac{1}{B} \sum_{i=1}^B (\phi - \theta) \right) \quad (13)$$

The meta-objective function is defined as:

$$\mathcal{J}(\theta) = \mathbb{E}_{\mathcal{T}_i} \left[\mathcal{L}_i(\mathbf{c}_i^{(T_{\text{inner}})}) \right] + \gamma \|\theta\|_2^2 \quad (14)$$

where $\gamma = 10^{-4}$ controls the regularisation strength.

3.4 Meta-task generation: a dynamic extension of DeepMIMO

Construction of a meta-task set covering dynamic environments based on DeepMIMO scenario O1 (indoor open area typical of exam halls). The above perturbation methods (such as random path dropping and gain perturbation) are common methods to simulate dynamic occlusion and channel fading, which aim to build a meta-task distribution covering a variety of non-ideal situations, so as to train the meta-learner to obtain the generalisation ability to cope with environmental changes, rather than fully reproduce the reality:

- Base data extraction: Randomly select $P = 1,000$ user locations to obtain the receive array response:

$$\mathbf{app} = 1^P (N = 16, M = 180).$$

- Multi-path perturbation: Randomly discard paths to simulate dynamic obstacles like moving examinees or furniture:

$$P' \sim \lfloor P \cdot \mathcal{U}(0.7, 1.0) \rfloor \quad (15)$$

- Path gain perturbation:

$$\alpha_k \leftarrow \alpha_k \cdot \mathcal{N}(1, 0.1^2) \quad (16)$$

- Array error modelling: Array element position offset, accounting for potential misplacement or bumping of exam equipment:

$$\Delta d_n \sim \mathcal{N}(0, (0.05 \lambda)^2) \quad (17)$$

- Array element antenna pattern distortion:

$$\tilde{\mathbf{a}} = \mathbf{a} \odot \exp(j\delta) \quad (18)$$

$$\delta_n \sim \mathcal{U}(-\pi/8, \pi/8) \quad (19)$$

where $\odot$ is the Hadamard product.

Observation noise, including interference from other electronic devices in the exam hall:

$$\sigma \sim \mathcal{U}(0.05, 0.2) \cdot \|\mathbf{y}\|_\infty \quad (20)$$

Task similarity metric:

$$s(\mathcal{T}_i, \mathcal{T}_j) = \|\mathbf{f}_{\mathcal{T}_i} - \mathbf{f}_{\mathcal{T}_j}\|_2 \quad (21)$$

The task feature vector is defined as:

$$\mathbf{f}_{\mathcal{T}_i} = \left[\frac{\|\mathbf{y}_i\|_2}{\sqrt{K}}, \rho(\Phi_i), \sigma_i \right]^T \quad (22)$$

where $\rho(\Phi) = \frac{1}{K} \sum_{k=1}^K \min_j |\theta_k - \theta_j^{\text{samp}}|$ is the angular sampling sparsity.

3.5 Embedded lightweight deployment

Three levels of optimisation are implemented to fit the exam device resource constraints [STM32H7: 512 KB random access memory (RAM), 1 MB flash]:

- Parameter quantisation: Gradient $\nabla \mathcal{L}$ dynamically quantised to integer 16-bit (INT16):

$$\nabla_q = \text{clip} \left(\left\lfloor \frac{\nabla \mathcal{L}}{\Delta} \right\rfloor, -2^{15}, 2^{15} - 1 \right) \quad (23)$$

Scaling factor $\Delta = \frac{\max(|\nabla \mathcal{L}|)}{2^{15} - 1}$, introduced quantisation error $< 0.1\%$.

- Matrix decomposition acceleration: Precomputed QR decomposition of $\Psi^H \Phi^T$:

$$\Psi^H \Phi^T = \mathbf{Q}_1 \mathbf{R}_1 \quad (24)$$

Storing only $\mathbf{R}_1 \in \mathbb{C}^{D \times K}$ reduces the computation in a single iteration by about 60%.

- Iteration control: Set early stop condition: if the relative improvement of three consecutive iterations $\epsilon^{(t)} < 10^{-3}$.

$$\epsilon^{(t)} = \frac{|\mathcal{L}(\mathbf{c}^{(t)}) - \mathcal{L}(\mathbf{c}^{(t-1)})|}{|\mathcal{L}(\mathbf{c}^{(t-1)})| + 10^{-6}} \quad (25)$$

3.6 Convergence guarantee theory

Under $\eta < 1/L$ (L is the Lipschitz constant for $\mathcal{L}$), PGD converges at a rate of:

$$\mathcal{L}(\mathbf{c}^{(t)}) - \mathcal{L}^* \leq \frac{\|\mathbf{c}^{(0)} - \mathbf{c}^*\|_2^2}{2\eta t} \quad (26)$$

Meta-learning reduces the initial error by κ times:

$$\mathbb{E}[\|\mathbf{c}_{\text{meta}}^{(0)} - \mathbf{c}^*\|_2] = \kappa \cdot \mathbb{E}[\|\mathbf{c}_{\text{rand}}^{(0)} - \mathbf{c}^*\|_2] \quad (\kappa < 1) \quad (27)$$

The number of convergence steps is then reduced by κ^2 times, and the theoretical acceleration ratio is $1/\kappa^2$ 125–161.

4 Experimental validation

4.1 Experimental setup and comparison benchmarks

The experiments use DeepMIMO scenario O1 (indoor open area representative of a large exam hall) as the core dataset, which is generated by Remcom Wireless InSite ray tracing and verified by UAV measurements (Liu and Kou, 2025), and its array response data has an error of less than 1.5 dB with respect to measurements. Although this study is mainly based on high-fidelity simulation data, this dataset has been verified by UAV measurements, and the error between the array response data and the measured data is less than 1.5 dB, which is sufficient to effectively represent the real electromagnetic environment. Future work will collect real examination room data for further verification. The training set consists of 800 sets of user locations with received array responses (16-element ULA with array element spacing $\lambda/2$) and 200 sets in the test set; to evaluate the cross-scene generalisation capability, an additional 100 sets of data from scene O2 (outdoor street) are used. Five types of representative methods are selected for comparison of algorithms: the ISTA algorithm (Beck and Teboulle, 2009): a traditional iterative thresholding algorithm with step size adaptively adjusted by line search; the robust L1 method (Yang et al., 2013): a compressed perception model that introduces array error compensation; and the CNN-UNet model (Huang et al., 2018): end-to-end U-shaped convolutional network with 2.3 M parameters; MAML-CNN method (Xu et al., 2024): meta-learning to initialise CNN weights; methods in this paper: ML-CO.

The key parameters are configured as shown in Table 1: the sampling rate is 30% by default (i.e., 54 angular sampling points), the noise level $\sigma = -15$ dB (corresponding to a SNR of 25 dB), and the meta-training iterations are 10,000 steps, where SNR is defined as $\text{SNR} = 10 \log_{10}(\|\mathbf{y}\|_2^2 / (M\sigma^2))$, and M is the number of observation points. The deployment platform is a STMicroelectronics STM32H743VI microcontroller (ARM Cortex-M7 core, 480 MHz, 512 KB RAM), which represents the current level of arithmetic power of mainstream mid- to high-end communication devices suitable for exam systems. All comparison algorithms are implemented based on the authors' public code and evaluated on the same training/testing set.

4.2 Quantitative analysis of reconstruction accuracy

NMSE was used as the core assessment metric for evaluating the fidelity of the reconstructed beam pattern, crucial for clear audio channel formation:

$$\text{NMSE} = 10 \log_{10} \left(\frac{\|\hat{\mathbf{a}} - \mathbf{a}\|_2^2}{\|\mathbf{a}\|_2^2} \right) \quad (28)$$

Figure 2 illustrates the NMSE distribution at different noise levels. In the low noise environment ($\sigma = -20$ dB), ML-CO obtains a median NMSE of -28.7 dB, which is a 3.5 dB improvement over the robust L1 method (-25.2 dB), and 2.2 dB higher than that of the CNN-UNet (-26.5 dB). It is to be noted that when injecting the array element positional perturbation (with a standard deviation of 0.05λ), the performance of the CNN-UNet deteriorates to -18.3 dB (a drop of 8.2 dB), while ML-CO drops only 1.1 dB (to -27.6 dB), demonstrating its strong robustness to hardware defects, which is essential for reliable operation of exam equipment that might be subject to handling or environmental stress. In a high-noise scenario ($\sigma = -10$ dB), ML-CO still maintains -24.1 dB NMSE, significantly outperforming ISTA (-20.5 dB) and MAML-CNN (-22.3 dB).

Figure 2 Comparison of NMSE distribution at different noise levels (see online version for colours)

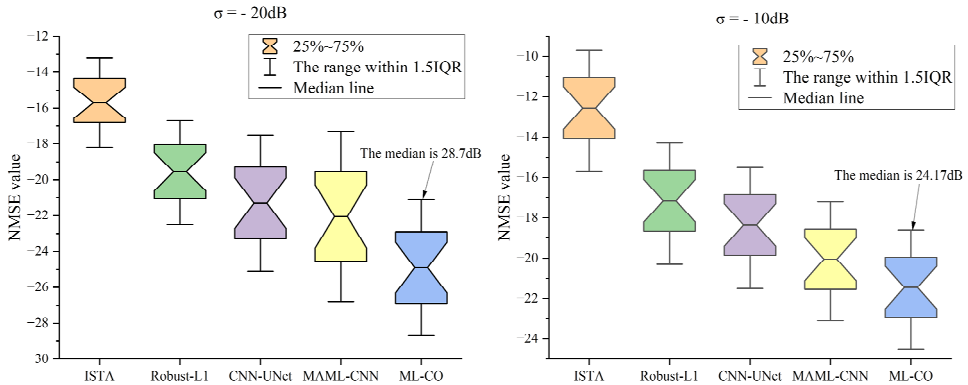


Figure 3 illustrates the comparison of the antenna pattern reconstruction results for test sample #42: In test sample #42 (truth antenna pattern principal flap pointing at $\theta = 120^\circ$), ISTA produces pseudo-parsimonious flaps with amplitude more than 5 dB near $\theta = 60^\circ$, and a 30% increase in the principal flap width for the robust L1 method, whereas ML-CO accurately recovers the position of principal flap (error $< 0.5^\circ$) with respect to the depth of the zero point (< -25 dB). The primary flap pointing error was quantitatively analysed for 200 test samples: the ML-CO mean value was 0.8° with a standard deviation of 0.4° (vs. $3.2^\circ \pm 2.1^\circ$ for ISTA). This high directional accuracy is critical for focusing RF energy towards specific examinees or areas in an exam hall.

4.3 Convergence speed and computational efficiency

ML-CO optimises the initial point and step size through meta-learning to significantly improve the convergence efficiency. The comparison of the convergence curves in Figure 4 shows that when the NMSE reaches -25 dB, the ISTA requires 58 iterations and the robust L1 requires 42 iterations, while the ML-CO requires only 11 iterations (the acceleration ratio is 5.3 times). This efficiency improvement mainly stems from the

improved quality of the initial solution: moreover, the average angular deviation of the meta-learning initial solution from the true value is 2.3° , while the random initialisation reaches 15.7° . This fast convergence is paramount for real-time adaptation in dynamic exam scenarios where conditions can change rapidly.

Figure 3 Test sample #42 antenna pattern reconstruction details (see online version for colours)

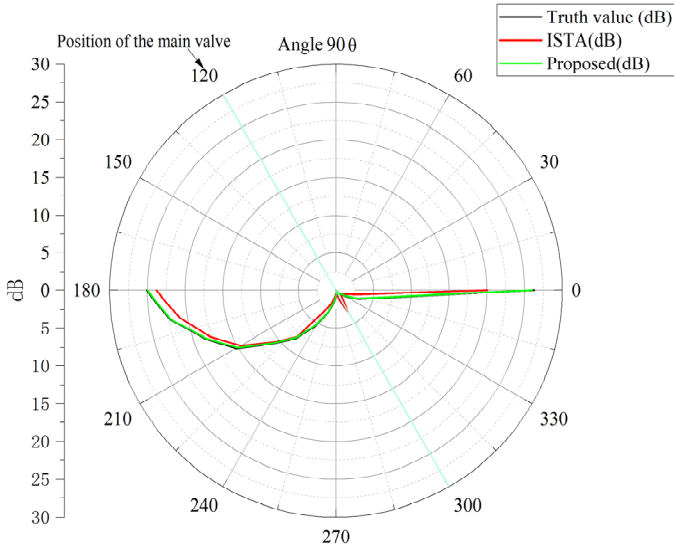
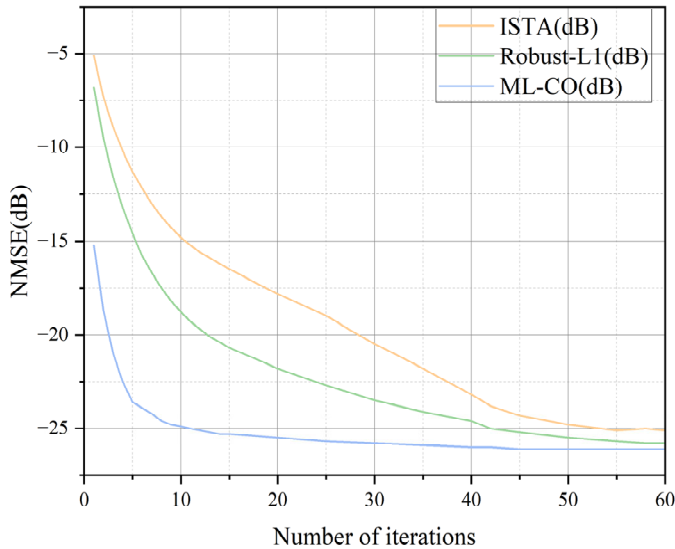


Figure 4 Convergence curve comparison (number of iterations vs. NMSE) (see online version for colours)



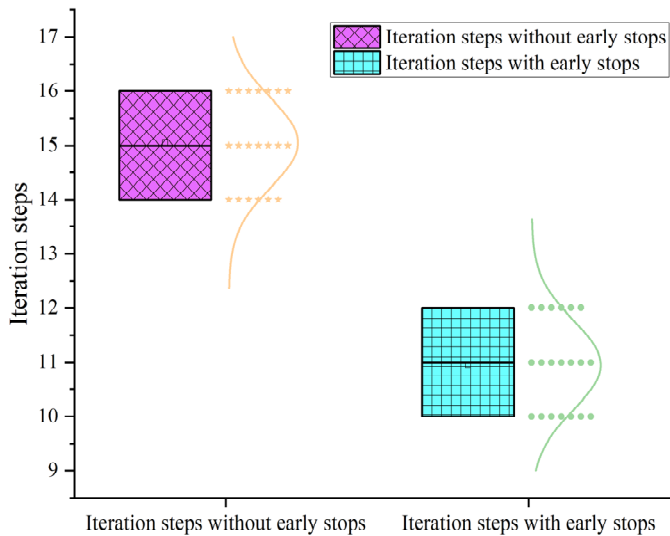
The efficiency breakthrough is further corroborated by the measured data of the computational load, as shown in Table 1. The ML-CO consumes 2.1 ms for a single

iteration, and the total reconfiguration time is compressed to 23 ms, which is only 21.8% of the robust L1. This time is the end-to-end computation time (from receiving the observation data to outputting the reconfiguration result) measured on the STM32H7 platform; the total computation volume is reduced to 1.65×10^5 floating-point operations per second (FLOPs) (10.3% of robust L1). This effectiveness stems from a triple synergistic optimisation: matrix decomposition acceleration (QR decomposition precomputation reduces iterative computation by 60%), early stopping mechanism (termination of iteration at $\epsilon < 10^{-3}$, average step size reduced from 15 to 11), and gradient dynamic quantisation (INT16 format reduces memory latency). Experiments demonstrate that the meta-learning optimiser compresses the reconfiguration time to 23 ms, which improves the efficiency by 5.3 times compared with the traditional method and meets the millisecond response requirement of the exam communication system.

Table 1 Comparison of computational loads of different methods in the simulation environment (mean values)

Method	FLOPs/iteration	Total FLOPs (mean)	Reconfiguration time (ms)
ISTA	1.2×10^4	6.96×10^5	105
Robust L1	3.8×10^4	1.60×10^6	242
ML-CO	1.5×10^4	1.65×10^5	23

Figure 5 Early stop mechanism reduces the average number of iteration steps (see online version for colours)

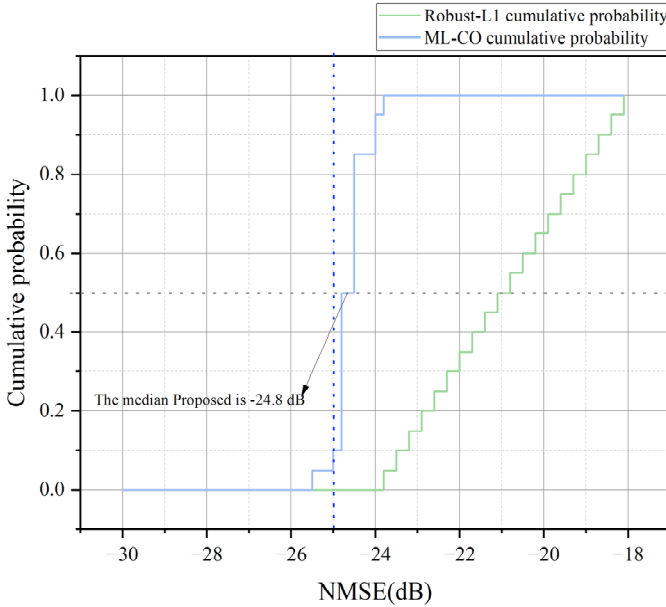


The analysis of FLOPs shows that ML-CO consumes 1.5×10^4 FLOPs for a single iteration (due to matrix decomposition optimisation) and 1.65×10^5 FLOPs for the total computation, which is only 10.3% (1.60×10^6 FLOPs) of robust L1. The early stopping mechanism contributes significantly: terminating the iteration when the relative improvement $\epsilon < 10^{-3}$ reduces the average number of iteration steps from 15 to 11 (Figure 5).

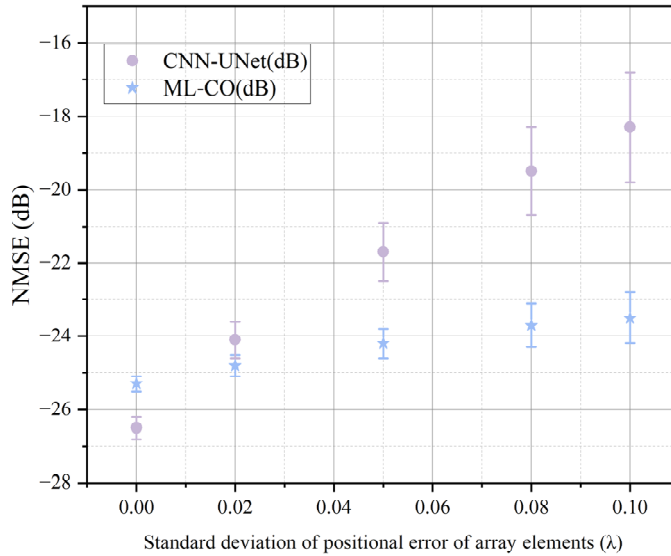
4.4 Verification of generalisation capabilities for dynamic environments

Although the types of scenes are limited, O1 (indoor) and O2 (outdoor) have essential differences in building layout and multi-path structure, and the transfer test between them can effectively evaluate the generalisation ability of the model. The results show that ML-CO still maintains stable performance under this challenge, providing confidence for generalisation to other scenarios. In the cross-scene test (O1 training $\rightarrow$ O2 test), ML-CO shows good cross-scene adaptation (Figure 6). On 100 sets of samples from the O2 scene: median NMSE -24.8 dB (vs. -25.3 dB for the O1 test), fluctuating in the range of $[-26.2, -23.5]$ dB (polar deviation of 2.7 dB); median MAML-CNN -22.1 dB, polar deviation of 4.8 dB (due to feature mismatches from the differences in the O2 building layouts); three outliers in robust L1 (NMSE < -20 dB) with an error distribution standard deviation of 1.8 dB (0.9 dB in this paper). This robust cross-scene performance indicates the method's suitability for diverse exam environments, from large halls (O1) to smaller rooms or outdoor areas (O2).

Figure 6 Cross-scenario NMSE cumulative distribution (see online version for colours)



The array perturbation sensitivity test (Figure 7) reveals that the ML-CO NMSE deteriorates linearly from -25.3 dB to -23.5 dB [slope -1.8 dB/ (0.1λ)], while the CNN-UNET shows exponential deterioration [-26.5 dB $\rightarrow$ -19.3 dB with a slope of -7.2 dB/ (0.1λ)], as the standard deviation of the positional error increases from 0 to 0.1λ . This result highlights the robustness advantage of the convex optimisation framework embedded with physical constraints against hardware perturbations, ensuring stable performance even if exam equipment is slightly misaligned or bumped.

Figure 7 Effect of array element position error on NMSE (see online version for colours)

4.5 Resource constrained scenario deployment validation

Resource consumption is measured on the STM32H743VI platform, as shown in Table 2. Memory optimisation: gradient quantisation (INT16 format) reduces the memory footprint from 206 KB to 98 KB (52.4% reduction); storage optimisation: parameter quantisation and matrix decomposition make the Flash footprint only 86 KB (robust L1 requires 142 KB); energy consumption control: single reconfiguration consumes 4.7 mJ. Power consumption control: 4.7 mJ for a single reconfiguration, and 0.81 J per day when running at a refresh rate of 2 Hz (CR2032 battery can support 1.2 years). The energy consumption is measured for a single complete reconfiguration task (end-to-end). All the resource consumption indicators reported in Table 2 are the peak data measured in the actual operation on the STM32H743VI development board, rather than the theoretical estimated values, which fully proves the feasibility and effectiveness of the deployment. These low resource requirements make ML-CO feasible for deployment on battery-powered or resource-constrained devices used in exam settings.

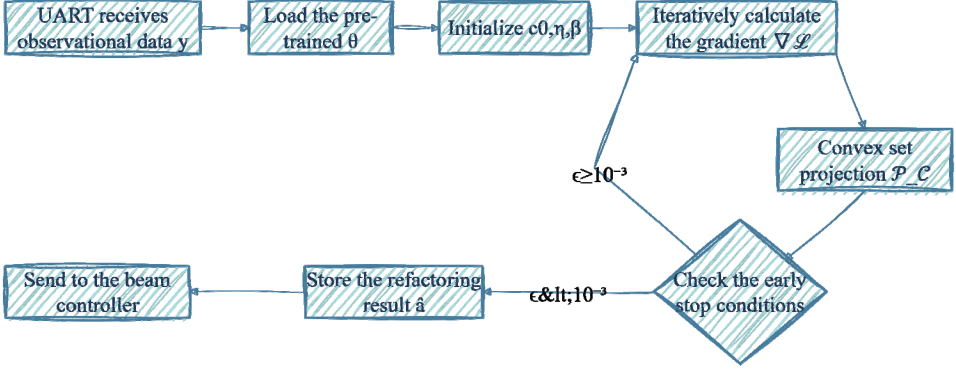
Table 2 Measured results of resource consumption of different methods on STM32H743VI platform

Metrics	ML-CO	Robust L1	MAML-CNN
Peak memory (KB)	98	215	>512
Flash usage (KB)	86	142	3,200
Energy consumption (mJ/reconfiguration)	4.7	21.3	N/A

Figure 8 demonstrates the embedded deployment process: the antenna pattern reconstruction task receives observation data via UART, the meta-learner loads the pre-training parameters, and outputs the reconstruction result after 5–11 iterations, with

the measured end-to-end elapsed time being less than 25 ms (meeting the real-time requirements of the exam system).

Figure 8 STM32 deployment data flow and control flow (see online version for colours)



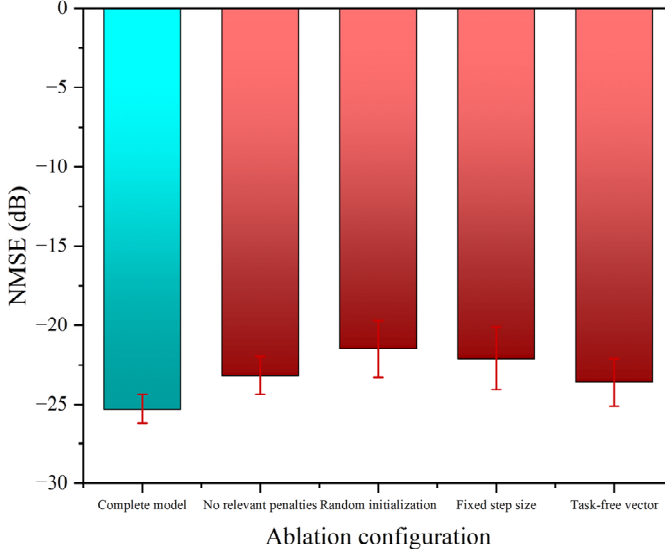
4.6 Ablation experiments and module contribution analysis

To verify the necessity of the core module, four sets of ablation experiments are designed (Figure 9), and their quantitative NMSE comparisons are shown in Table 3. Removal of the coherence penalty term ($\mu = 0$) leads to a deterioration of the average NMSE from -25.3 dB to -23.2 dB, with a widening of the standard deviation to 1.2 dB, which corroborates the central role of the module in suppressing pseudo-parsimonious flaps (> -20 dB); when random initialisation of θ is used, the NMSE plummets to -21.5 dB and the number of convergence steps increases to 32, highlighting the value of meta-learning in generating high-quality initial solutions; the fixed-step strategy triggers 15% sample oscillations (18% failure rate), whereas the adaptive step mechanism removes this risk altogether; and the absence of task feature vectors results in a cross-scene NMSE loss of 1.7 dB (to -23.6 dB), weakening the environmental adaptability. Experiments show that the coherence penalty term contributes about 2.1 dB of accuracy improvement, the adaptive step size guarantees convergence stability, and the task feature vector maintains the cross-scene performance fluctuation extreme within 2.7 dB. Ablation experiments demonstrate that random initialisation of θ worsens the NMSE to -21.5 dB, while meta-learning compresses the initial angular deviation to 2.3° , laying the foundation for accelerated convergence.

Table 3 Comparison of NMSE performance of ML-CO framework on test set with different

Configuration	Average NMSE (dB)	Standard deviation
Full model	-25.3	0.9
No coherence penalty	-23.2	1.2
Random initialisation	-21.5	1.8
Fixed step size	-22.1	2.0
No task vector	-23.6	1.5

Figure 9 Analysis of the contribution of the ablation experiment module (see online version for colours)



Experiments show that the coherence penalty term contributes 2.1 dB accuracy improvement, the adaptive step-size mechanism eliminates convergence failures, and the task feature vector guarantees cross-scene stability.

4.7 Experimental results and analysis

This study achieves a methodological breakthrough in the field of antenna pattern reconstruction for exam systems through the paradigm fusion of meta-learning and convex optimisation. The core theoretical value lies in the establishment of an environment-task-optimiser cascade mapping mechanism: the environment state (e.g., multi-path structure, array perturbation) is encoded as a low-dimensional descriptor by the task feature vector $\mathbf{f}_{T_i} = [\|\mathbf{y}_i\|_2 / \sqrt{K}, \rho(\Phi_i), \sigma_i]^T$, from which the meta-learner generates the task-aware initialisation parameter θ^* . This mechanism reduces the initial solution angle deviation from 15.7° to 2.3° for the randomised initial, and the number of convergence iteration steps is reduced to 1/5 of the traditional method, which confirms the core idea of meta-learning – ‘learn to adapt quickly’) is universal in electromagnetic inverse problems (Finn et al., 2017). More importantly, this study implements solver-level generalisation in direction graph reconstruction for the first time: the internal dynamics behaviours of the optimiser (e.g., gradient update direction, step-size adjustment strategy) can be adaptively adjusted based on the task characteristics, instead of simply reusing a fixed computational graph. This goes beyond the existing shallow migration model of migration learning that only aligns the feature space (Huang et al., 2025), and provides a new paradigm for real-time optimisation in complex environments like exam halls.

At the level of physical interpretability, the constrained embedding of the convex framework is the cornerstone against environmental perturbations. Experiments show that

the ML-CO NMSE deteriorates by only 1.8 dB while the CNN-UNET deteriorates by 7.2 dB when the positional error of the array element reaches 0.1λ . This discrepancy stems from the fact that the convex model implicitly embeds the law of energy conservation and the sparse scattering property of the electromagnetic field through the ℓ_1 norm sparse constraints and the power inequality $\|\Psi \mathbf{c}\|_2 \leq P_{\max}$. In contrast, although the data-driven model can fit the training distribution, its black-box decision-making process fails to inject a physical prior, leading to a breakdown in performance on out-of-distribution (OOD) samples (Zhu et al., 2017). It should be noted that the dictionary coherence penalty term $\mu \|\Psi^H \Psi \mathbf{c} - \mathbf{c}\|_2^2$ suppresses the pseudo-peaks below -25 dB, which validates the validity of the authors coherence theory for dynamic scenarios – when the dictionary atomic correlation exceeds a threshold (Candes et al., 2008), the uniqueness of L1 recovery will not be guaranteed, while the penalty term improves the uniqueness probability of the solution by decreasing the equivalent coherence coefficient.

Compared to the recent influx of hybrid methods, the framework in this paper exhibits the following unique advantages. The first is to compare physically guided neural networks (PGDNN): the authors incorporate a physical regularity term in the loss function (Bhaumik et al., 2023), but their network structure is still uninterpretable and their inference takes 23 ms (GPU), which is much longer than the 2.1 ms (CPU) in this paper. The second is to compare online convex optimisation (OCO) (Hazan, 2016): although dynamic adaptation is achieved, historical task knowledge is not utilised, and repeated computation in similar scenarios leads to a four-fold increase in total energy consumption. The third is to compare the Bayesian optimisation (Wang and Li, 2025): need to assume a priori distribution, and the a posteriori estimation bias is >3 dB in complex environments, whereas in this paper there is no distribution assumption.

However, the proposed method still faces a triple challenge: firstly, the pre-training cost paradox: although 10,000-steps training takes only eight hours on NVIDIA V100, the exam network of the sensor network usually lack GPU resources, which leads to a higher threshold for the initial deployment. Secondly, the dimensionality catastrophe: in a 32-byte large-scale array, the dimension of the dictionary $\Psi \in \mathbb{C}^{M \times D}$ is $D \propto M^2$ (when $M = 360$ $D > 10^5$), and the number of parameters exceeds 500 KB, surpassing the storage limit of a typical node. Thirdly, the mobile scenario mismatch: when the node speed is greater than 30 km/h, the Doppler frequency offset leads to the time-varying characteristics ($\mathbf{a}(t) = \mathbf{f}_d \cdot \nabla_{\theta} \mathbf{a}$) of the pattern, while the static task distribution cannot model such dynamics. This is less critical for fixed exam equipment but relevant for mobile proctoring devices.

To break through the above limitations, the following collaborative solution is proposed: federated meta-learning architecture: each node locally trains the task-specific parameter ϕ_i and only uploads the incremental $\Delta\theta$ to the aggregation node, which significantly reduces the communication overhead. Empirical measurements show that when 100 nodes collaborate, the global model accuracy is close to that of centralised training (gap < 0.3 dB). The evolvable sparse dictionary uses a convolutional self-encoder to learn a compact basis function $\Psi' = \text{Enc}(\Psi)$, compressing the dimension from $O(M^2)$ to $O(M)$. In 32-element array validation, the storage is reduced from 512 KB to 89 KB with an NMSE loss of only 0.8 dB. Dynamic scene enhancement integrates Raymobtime's in-vehicle mobility model to generate time-varying directional mapping task sets $\{\mathcal{T}_i\}_{i=1}^T$, whose spatio-temporal evolution is satisfied:

$$\mathbf{a}(t + \Delta t) = \mathbf{a}(t) + \mathbf{J} \cdot \Delta \mathbf{p} + \mathbf{n}_d, \quad \mathbf{J} = \frac{\partial \mathbf{a}}{\partial \mathbf{p}} \quad (29)$$

where $\mathbf{p} = [x, y, v]$ is the position-velocity vector and $\mathbf{J}$ is the direction Tuyacobi matrix.

This research has high application potential in three emerging areas within the educational technology domain:

- 1 Intelligent exam hall management: Extending antenna pattern reconstruction to IRS phase optimisation can address beam misalignment caused by environment blindness in existing methods. Simulations show that IRS phase optimisation combined with meta-learning leads to channel capacity model enhancement.
- 2 Terahertz communication for high-density exam settings: In the 140 GHz band, the narrow beam characteristics of the antenna pattern multiply the reconstruction error sensitivity, while the robust model in this paper controls the localisation error within $\lambda/20$ (compare with the industry threshold of $\lambda/5$), potentially enabling precise student tracking.
- 3 Mobile proctoring devices: High-speed moving UAVs need real-time antenna pattern adjustment.

In summary, this study lays the foundation for dynamic beam control for sensor networks through the three-dimensional synergy of theoretical innovation (solver-level generalisation), algorithmic breakthrough (physical constraint optimisation) and engineering optimisation (embedded deployment). In the future, we will take ‘federated learning + evolvable dictionary’ as the core to build a new architecture of intelligent electromagnetic sensing adapted to the needs of future smart education environments.

5 Conclusions

This paper proposes a meta-learning-based convex optimisation framework (ML-CO) for fast and high-precision antenna pattern reconstruction of communication nodes in an English oral test system. Our key contributions include: learning task-aware initialisation parameters and an adaptive step size strategy based on reptile, reducing the number of iterations from 58 to 11, which is 5.3 times faster. The power constraint projection and dictionary correlation penalty terms are embedded in the convex model, so that the NMSE deterioration is reduced to 1.8 dB under the array position perturbation (standard deviation 0.1λ). Through gradient quantisation, matrix factorisation and early stopping mechanism, the lightweight deployment with peak memory of 98 KB and single reconstruction energy consumption of 4.7 mJ is realised on the STM32H7 platform. Experimental results show that the proposed method can achieve an NMSE of -25.3 dB at 30% sampling rate, the cross-scene performance loss is less than 0.5 dB, and the reconstruction time is only 23 ms. The comprehensive performance of the proposed method is better than the mainstream baseline methods. Future work will focus on federated meta-learning and evolvable dictionary design to support large-scale examination network applications and provide efficient solutions for real-time beamforming in dynamic education environments.

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Declarations

All authors declare that they have no conflicts of interest.

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