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A Hybrid Prediction-Axiom Dual-Driven Port Selection Algorithm for Fluid Antenna Systems in 6G High-Mobility Scenarios

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Abstract

A significant bottleneck for the practical deployment of fluid antenna systems (FASs) in 6G high-mobility scenarios is the conflicting demands of low outage probability and the high overhead of full port channel estimation. To resolve this problem, a novel “prediction-axiom” dual-driven paradigm is introduced that fundamentally differs from pure data-driven approaches. The core innovation lies in using an enhanced unified adaptive modeling algorithm (UAMA) not for direct decision-making but as a computational foundation to enable information-theoretic axioms under sparse observation conditions (30% of ports). The UAMA predictor, leveraging spatiotemporal correlations, accurately reconstructs the full channel state from limited measurements. This prediction then empowers an information-theoretic scoring mechanism, which synergizes Fisher information, curvature metrics, and port entropy to transform optimal port selection into a tractable maximization problem. Consequently, the system outage probability remains close to the ideal performance limit achievable under full observability. Tests on diverse antenna systems confirm the algorithm’s high accuracy and robust adaptive capability. This work delivers a reliable, low-cost implementation strategy for 6G dynamic networks, effectively bridging the gap between mathematical theory and practical FAS deployment.

Keywords: fluid antenna system; port selection; channel prediction; hybrid algorithm; outage probability; mathematical axiom optimization

1. Introduction

FASs represent a paradigm shift in wireless communications, offering unprecedented flexibility through dynamic port switching. However, their practical deployment in 6G networks faces a fundamental trade-off: achieving low outage probability requires frequent channel estimation, yet full-port measurement imposes prohibitive overhead, especially in high-mobility scenarios. In this work, we explicitly define “high mobility” as scenarios with a characteristic velocity of 30 km/h, representing a practical and typical baseline for vehicle-to-vehicle networks and pedestrian-level mobility in dense urban environments. This velocity captures the typical Doppler shift and temporal correlation observed in city-scale 6G deployments, enabling focused validation of the proposed algorithm under realistic dynamic conditions while maintaining manageability for comparative analysis. Higher speeds (>100 km/h) would exacerbate temporal variations, presenting opportunities for future extensions to further test the algorithms’ adaptability. This paper addresses this



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core challenge by proposing a novel “prediction-axiom” dual-driven framework that fundamentally rethinks how mathematical principles and deep learning can synergize for efficient FAS operation under sparse observations. Now, FASs have emerged as a key technology for enhancing spectrum efficiency and reliability. By overcoming traditional hardware limitations through rapid switching of spatial ports, FASs enable significant advancements in network performance. As highlighted in the systematic review [1], the accuracy of FAS channel modelling and the real-time nature of port selection are becoming critical to research as 6G networks evolve to higher frequency bands and dynamic operation.

Channel modeling must capture the complex multipath scattering characteristics of millimeter-wave bands, while port selection must balance computational overhead and system robustness within millisecond-level response times. In multi-user and large-scale scenarios, achieving efficient channel prediction and port decisions based on sparse observations represents the core challenge for transitioning FAS technology from theory to practical deployment.

In channel modeling, Psomas [2] constructed a closed-form model for the spatial correlation of continuous FAS, quantifying the impact of antenna size and elevation angle on channel attenuation. Khammassi [3] proposed a novel channel approximation method that reduces the computational complexity of high-dimensional parameters. For port selection algorithms, Chai [4] designed a heuristic approach based on information geometry theory. Notably, Zhang [5] introduced an innovative fast port selection algorithm using spatiotemporal joint optimization, achieving low resource consumption and high accuracy in high-speed scenarios. However, at a measurement interval of 50, the outage probability curve deteriorated significantly, and the algorithm struggled to balance robustness and computational overhead in multi-user, large-scale antenna systems.

The algorithm dynamically balances exploration and exploitation through curvature factors, maintaining low outage probability under sparse measurements. Xu [6] further revealed the coupling mechanism between interference and outage probability in multi-user scenarios, providing theoretical support for anti-interference design. In large-scale AI model algorithms, Belgiovine [7] developed a lightweight edge inference model that reduces delay in massive multiple-input multiple-output (MIMO) channel estimation.

Huang [8] and Chun [9] improved modeling accuracy through super-resolution estimation and low signal-to-noise ratio optimization, respectively. Zero-shot learning methods [10] address data dependency challenges in dynamic environments, while attention mechanisms by Gao [11] and beam space compression techniques by He [12] reduce resource overhead. Li Hong [13] proposed a hybrid feature framework to validate the feasibility of the lightweight algorithm.

Furthermore, index modulation techniques have emerged as a promising approach to enhance spectral efficiency by exploiting antenna indices for additional information transmission. For example, Index Modulation Multiple Access (IMMA) [14] extends non-orthogonal multiple access by utilizing index patterns across domains (e.g., time, space) to support massive connectivity in 6G networks, while spatial modulation (SM) [15] leverages antenna activation states to achieve energy-efficient communication.

These methods highlight the potential of port selection in FAS not only for channel estimation but also for implicit data conveyance, which could further reduce outage probability. However, most existing index modulation schemes rely on full or dense channel measurements, limiting their adaptability in high-mobility scenarios with sparse observations.

Although the utilisation of spatio-temporal correlations has emerged, a theoretical framework for balancing exploration and exploitation under uncertainty remains lacking. Our work addresses this gap by introducing an information-score mechanism that

systematically integrates geometric and entropic metrics of prediction accuracy with channel dynamics.

Unlike pure data-driven models, our method grounds port selection in information-theoretic axioms, using a deep learning-enhanced predictor (UAMA) not for direct decision-making, but to enable these mathematical principles under sparse observations [16]. This fusion ensures robustness and interpretability.

The comparative analysis in Table 1 critically positions our work against key prior arts. While existing methods either require high measurement ratios or show limited robustness under mobility, the UAMA-based information-score framework achieves a superior balance. It maintains low measurement overhead (30%) while delivering exceptional robustness in high-mobility scenarios, fulfilling a critical gap for practical FAS deployment. This demonstrates our work's unique advantage in enabling reliable, low-overhead port selection where previous approaches fall short.

Table 1. The brief comparative table; our work is very necessary.

Reference	Core Methodology	Required Observation Ratio	Robustness to Mobility
[4]	Smart “Predict and Optimize” (SPO)	10%	not possessing
[5]	Long Short-Term Memory (LSTM)	30%	a degree of robustness
[7]	Multi-Layer Perceptron (MLP)	100%	limited robustness
[10]	Deep Neural Network (DNN)	only at the pilot position	not possessing
This work	UAMA + Information-score	30%	exceptional robustness

Our contributions extend beyond the algorithmic framework to include comprehensive validation and practical insights. We demonstrate through extensive simulations that the proposed method achieves outage probability performance approaching the ideal limit achievable under full observability, even with large antenna sizes and high mobility. More importantly, we provide a detailed analysis of why and how the method works: we show how the information scoring mechanism adapts to different mobility scenarios, how the UAMA prediction accuracy degrades gracefully with increasing measurement intervals, and how the framework generalizes across different antenna configurations. These insights are critical for practical deployment, as they provide system designers with clear guidelines on when and how to apply the method. Python simulations demonstrate that even with an antenna size scaled to 5λ and high measurement intervals, the outage probability of this method approaches the ideal performance limit under fully observable conditions, achieving greater robustness while reducing computational overhead.

The remainder of this paper is organized as follows: Section 2 details the FAS system model and the mathematical formulation of the port selection problem. Section 3 introduces the UAMA prediction mechanism and its architectural design, and then presents the information-theoretic scoring framework and the complete hybrid algorithm. Section 4 provides comprehensive simulation results and analysis, including comparisons with state-of-the-art baselines and sensitivity studies. Section 5 discusses practical applications to real antenna systems and implementation considerations. Finally, Section 6 concludes this paper and outlines future research directions.

2. Fluid Antenna System

2.1. System Model

This paper considers a typical point-to-point communication system where the transmitter uses a standard antenna and the mobile receiver employs a fluid antenna. The fluid antenna can switch its radiating elements to any of N preset positions (ports) uniformly

distributed along a linear space of length $W\lambda$, where λ is the wavelength. The received signal at the k -th port is expressed as follows.

$$Z_k = h_k \cdot x + \eta_k, \quad (1)$$

where h_k denotes the complex channel coefficient for port k , following a complex Gaussian distribution with mean zero and variance M , and η_k represents complex Gaussian noise with mean zero and variance σ_η^2 . The information symbol is denoted by x . The average signal-to-noise ratio (SNR) for each port is given by the following:

$$\text{SNR}_{\text{avg}} = M \cdot \mathbb{E}[|x|^2] / \sigma_\eta^2. \quad (2)$$

A Rician fading model incorporates spatial correlation, including direct and scattered components. We have the following:

$$h_k(t) = h_{\text{dir},k}(t) + h_{\text{scat},k}(t). \quad (3)$$

The spatial phase term is derived from the array geometric phase; we have the following:

$$\Phi_{s,k}(\theta, \phi) = 2\pi k (d/\lambda) \sin\theta \cos\phi, \quad (4)$$

where $D = W\lambda/(N - 1)$ is the port spacing, W is the antenna size (a multiple of the wavelength), $\theta \sim \mathcal{U}(0, 2\pi)$ is the azimuth angle, and $\phi \sim \mathcal{U}(0, 2\pi)$ is the elevation angle. Time correlation includes Doppler shift and autocorrelation filtering. The Doppler phase term can be written as follows:

$$\Phi_d(\theta, \phi, t) = 2\pi f_d t \cdot \sin\theta \cos\phi, \quad (5)$$

where $f_d = v/3.6\lambda$ is the maximum Doppler frequency, and v is the moving speed. Thus, the complete phase expression is as follows:

$$\Phi_{\text{total},k}(\theta, \phi, t) = \Phi_{s,k}(\theta, \phi) + \Phi_d(\theta, \phi, t). \quad (6)$$

Autocorrelation function filtering is applied to the original channel sequence. The final channel estimate is given by the following:

$$h_{\text{final},k}(t) = \sum_{\tau=0}^t R(\tau) \cdot h_k^{(0)}(t - \tau), \quad (7)$$

where $R(\tau) = P/2 \times J_0(2\pi f_d \tau)$ is the autocorrelation function, J_0 is the zero-order Bessel function of the first kind, $\tau = n \times T_{\text{slot}}$ is the time delay, and $T_{\text{slot}} = 66.67 \mu\text{s}$ is the time slot length. The feedback channel coefficient components are defined by the following:

$$h_{\text{dir},k}(t) = [\sqrt{(K/K+1)}] \exp[j(\alpha - 2\pi k (d/\lambda) \sin\theta_0 \cos\phi_0 - 2\pi f_d t \cdot \sin\theta_0 \cos\phi_0)] \quad (8)$$

and

$$h_{\text{scat},k}(t) = \sum_{l=1}^{N_p} \alpha_l \exp[-j(2\pi k (d/\lambda) \sin\theta_l \cos\phi_l + 2\pi f_d t \cdot \sin\theta_l \cos\phi_l)]. \quad (9)$$

2.2. UAMA—Prediction

The UAMA can be intuitively understood as a “channel imager”. It functions by taking a sparse, instantaneous snapshot (e.g., measurements from only 30% of the ports) and learns to reconstruct the full channel state. This is achieved by leveraging the inherent spatial correlations between different ports, captured by the Transformer component, and

the underlying temporal smoothness of the channel, which is learned by the convolutional decoder. Essentially, it intelligently fills in the gaps from the limited measurement, much like constructing a complete image from a partial view.

The UAMA model takes an input vector of measured channel amplitudes from a subset of ports and outputs predictions for all ports. Let $x_{\text{obs}} \in \mathbb{R}^M$ be the input vector containing amplitudes from M measured ports (where $M = 0.3 \times N$, and N is the total number of ports). The goal is to predict the full channel amplitude vector $y \in \mathbb{R}^N$.

The UAMA model consists of five modules. Pre-mapper maps the input to a high-dimensional space using a linear projection and a nonlinear activation. Formally, we have

$$h_{\text{pre}} = \text{GELU}(W_{\text{pre}}x_{\text{obs}} + b_{\text{pre}}), \quad (10)$$

where $W_{\text{pre}} \in \mathbb{R}^{D \times M}$ is a weight matrix, $b_{\text{pre}} \in \mathbb{R}^D$ is a bias vector, D is the embedding dimension (set to 32 in our experiments), and GELU is the Gaussian Error Linear Unit activation function. This enhances the nonlinear expression. Transformer Encoder captures spatial correlations between ports using multi-head self-attention. For the input h_{pre} , the self-attention mechanism is given by the following:

$$\text{Attention}(Q, S, V) = \text{softmax}(QS^T/\sqrt{d_k})V, \quad (11)$$

where Q, S, V are query, key, and value matrices derived from h_{pre} , and d_k is the dimension of keys. The output is normalized and passed through a feedforward network.

Mid-mapper reduces dimensionality to balance capacity and efficiency. It can be written as follows:

$$h_{\text{mid}} = W_{\text{mid}} h_{\text{pre}} + b_{\text{mid}}, \quad (12)$$

where $W_{\text{mid}} \in \mathbb{R}^{D/2 \times D}$ and $b_{\text{mid}} \in \mathbb{R}^{D/2}$. Decoder uses a 1D convolutional neural network (CNN) to extract local temporal features. The convolution operation is defined by the following:

$$h_{\text{dec}} = \text{RELU}(W_{\text{conv}} * h_{\text{mid}} + b_{\text{conv}}), \quad (13)$$

where $*$ denotes convolution, W_{conv} is a kernel, and padding is applied to maintain sequence length. Post-mapper maps the features back to the full-port amplitude predictions, which are given by the following:

$$y = W_{\text{post}} h_{\text{dec}} + b_{\text{post}}, \quad (14)$$

where $W_{\text{post}} \in \mathbb{R}^{N \times D}$.

The overall model is trained to minimize the mean squared error (MSE) between predictions and true amplitudes. We have the following:

$$L = 1/B \sum_{i=1}^B \| (y^{(i)} - y_{\text{true}}^{(i)}) \|^2, \quad (15)$$

where B is the batch size.

The UAMA model is trained on a comprehensive dataset generated from channel simulations, as detailed in Section 2.1 of this paper. The dataset encompasses multiple channel realizations across diverse scenarios, including varying antenna sizes W (ranging from 1λ to 6λ), mobility speeds v (e.g., 30 km/h for urban environments), and Rician factors K (defaulting to 10 for strong line-of-sight components). Each realization is generated using a Rician fading model that incorporates spatial and temporal correlations, with parameters such as the number of scatter paths $N_p = 5$, carrier frequency $f_c = 2.4$ GHz.

The channel coefficients are computed via Equations (3)–(9), ensuring realistic multipath characteristics. During training, the dataset is split into training and validation sets

with an 80% ratio, and input features are normalized channel amplitudes from 30% of the ports (e.g., 6 out of 20 ports, indexed as {0, 3, 7, 11, 15, 19} for uniform sampling).

The training process employs the Adam optimizer with a learning rate of 0.001, a batch size of 64, and 100 epochs, as specified in this paper. The model architecture, implemented in PyTorch, includes a pre-mapper with GELU activation, a transformer encoder for spatial attention, a mid-mapper for dimensionality reduction, a convolutional decoder for local feature extraction, and a post-mapper for output prediction. The embedding dimension is set to 32, and the MSE loss function is minimized between predicted and true channel amplitudes. Training convergence is monitored through smooth decreases in both training and validation loss curves, indicating no overfitting. This is achieved through early stopping and regularization techniques embedded in the model layers.

Generalization to unseen channel statistics is enhanced by the diversity of the training data, which covers a wide range of W , v , and K values. For instance, antenna sizes are varied from 1λ to 6λ , speeds from 10 km/h to 100 km/h, and Rician factors from 0 (Rayleigh fading) to 10 (strong LoS). This ensures robust performance across different environments, such as high-mobility scenarios or varying scattering conditions. During inference, the UAMA predictor takes sparse measurements (e.g., amplitudes from 30% of the ports) and outputs full-port predictions through forward propagation.

These predictions are leveraged by the information-theoretic scoring mechanism—integrating Fisher information, curvature factors, and port entropy—for optimal port selection. This decoupling of prediction and decision-making maintains low computational overhead while ensuring robustness, as demonstrated in the simulation results, where the outage probability approaches ideal performance even under sparse observations.

2.3. Port Selection

Port selection aims to maximize SNR based on prediction results. Mathematically, for each time slot t , we choose an optimal port k^* to maximize instantaneous SNR ($k \in \{1, 2, \dots, 20\}$), which can be calculated by the following:

$$K^* = \arg \max \text{SNR}_k(t), \quad (16)$$

where $\text{SNR}_k(t)$ is given by Equation (2). Since the channel gain $h_k(t)$ is not fully observable, only a subset of ports $h_{\text{obs}}(t)$ can be measured. For unobserved ports, the predicted value from UAMA is used. We construct a proxy objective function $f(k, t)$ to indirectly maximize $|h_k(t)|^2$. So, the eventual optimal port k^* can be expressed as follows:

$$K^* = \arg \max f(k, t). \quad (17)$$

As noted in [2], traditional mathematical methods offer stability and computational advantages. This paper proposes a hybrid port selection algorithm based on information geometry, differential geometry, and entropy balance mechanisms. The algorithm auto-updates parameters using the Fisher information matrix and curvature measurements [4].

3. Hybrid Algorithm Components

3.1. Fisher Information Matrix

The Fisher information matrix F measures the information carried by the channel state. A larger diagonal element $F[k, k]$ indicates greater uncertainty and variation at port k .

When port k is selected, the channel gain $h_k(t)$ is predicted, and the difference from the previous state $h_k(t-1)$ is written as $\delta_k = h_k(t) - h_k(t-1)$. The diagonal element is updated by the following:

$$\text{FisherInfo_k} = \beta F[k, k] + (1 - \beta) |\delta_k|^2, \quad (18)$$

where β is a forgetting factor. Ports with higher $F[k, k]$ values capture new channel peaks, implying greater $|h_k(t)|$.

The forgetting factor β (set to 0.5 in our simulations) is a critical parameter that controls the exponential weighting of historical Fisher information versus the instantaneous squared change $|\delta|^2$. Physically, it represents the memory depth of the algorithm—a higher β (closer to 1) places more weight on past states, promoting stability but potentially slowing adaptation to rapid channel variations. Conversely, a lower β (closer to 0) emphasizes recent changes, enhancing responsiveness but increasing susceptibility to noise.

The value $\beta = 0.5$ was selected to strike a balance between these competing demands. This choice ensures that the Fisher information matrix updates equally weighted historical trends and new evidence, providing robust adaptation across various mobility scenarios without requiring fine-tuning. It is a common default in recursive estimation techniques, offering a principled compromise between tracking agility and noise immunity.

3.2. Curvature Factor

Curvature(C_k) represents the rate of change of the channel state, quantifying the severity of variations. It is computed based on the measured δ , and we have the following:

$$C_k = |\delta(t) - \delta(t-1)|. \quad (19)$$

High C_k values indicate rapid changes, promoting exploration behavior to capture potential improvements.

3.3. Port Entropy

Port entropy(E_k) measures uncertainty. It is given by the following

$$E_k = -\log(F[k, k]). \quad (20)$$

Higher $F[k, k]$ implies lower uncertainty, so E_k is smaller. The `info_score` function incorporates E_k with a weight of 0.5 to balance exploration and exploitation.

3.4. Information Score

For each port k , the change score can be calculated by the following:

$$\text{change_score}_k(t) = |h_{\text{pred},k}(t)|^2 + C_k. \quad (21)$$

Here, $h_{\text{pred},k}(t)$ is the predicted channel gain from UAMA. Conceptualizing port selection as a pathfinding process, Fisher information theory quantifies the uncertainty inherent in a stock's recent price movements. This approach inherently favors assets with higher volatility, which are associated with greater potential returns. Concurrently, the curvature metric evaluates the acceleration of price changes, serving as an indicator of emerging trends. Finally, entropy measurements impose a constraint by discounting stocks characterized by excessive uncertainty. To integrate these three factors comprehensively, this paper ultimately proposes the composite attractiveness metric, `info_score`. The formula is written as follows:

$$\text{Info_score}_k(t) = \text{change_score}_k(t) + Y * E_k, \quad (22)$$

where $Y = 0.5$. The hybrid algorithm selects the port with the maximum `info_score`. The final flowchart of the joint UAMA-Hybrid algorithm is shown in Figure 1.

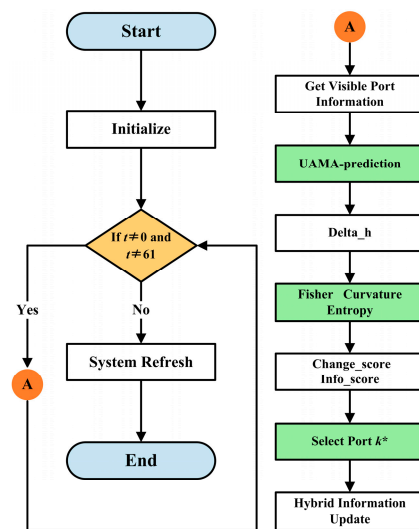


Figure 1. The hybrid algorithm flowchart has three factors to adapt to environmental changes in subsequent intervals.

The weighting parameter $Y = 0.5$ plays a pivotal role in balancing the exploration-exploitation trade-off inherent in the `info_score`. Physically, it quantifies the relative importance assigned to uncertainty reduction (via the port entropy E_k) compared to the immediate attractiveness of a port (via the `change_score`). A higher Y would prioritize exploration by favoring ports with higher uncertainty, potentially discovering new channel peaks but risking suboptimal choices in stable conditions.

A lower Y would emphasize exploitation by focusing on ports with high predicted SNR, improving short-term performance but potentially missing opportunities during transitions. The value $Y = 0.5$ was determined empirically through extensive simulations to maximize long-term outage probability performance across diverse scenarios (e.g., varying mobility, SNR). This value ensures that neither exploration nor exploitation is overly dominant, allowing the algorithm to dynamically adapt its strategy based on the predicted channel state. It represents a heuristic optimum where the marginal benefit of reducing uncertainty equals the marginal cost of forgoing immediate gains.

Theoretical analysis establishes that the information score maximization approximates the optimal SNR-based port selection strategy under three specific mathematical conditions that ensure the predictor's reliability and the channel's statistical properties.

First, the approximation holds when the UAMA prediction error $\varepsilon_k(t) = h_k(t) - \hat{h}_k(t)$ follows a zero-mean Gaussian distribution with variance σ^2 , which ensures that the predicted channel gain $|\hat{h}_k(t)|^2$ in the `change_score` term provides an unbiased estimate of the true SNR. Under this condition, the expected SNR satisfies $E[|h_k(t)|^2] = |\hat{h}_k(t)|^2 + \sigma^2$, making the `change_score` term directly proportional to the lower bound of the expected SNR. Second, the channel process must exhibit wide-sense stationarity over the observation window, guaranteeing that the spatiotemporal correlations learned by the UAMA predictor remain valid for the scoring mechanism. This stationarity ensures that the Fisher information matrix accurately captures the channel's variation patterns. Third, the channel should demonstrate ergodicity within the operational timeframe, allowing the time-averaged information score to converge to its ensemble average, thereby enabling the maximization operation to approximate the statistical optimum.

When these conditions are collectively satisfied, the curvature component C_k effectively tracks the channel variation trend while the entropy term E_k penalizes ports with high uncertainty, together enabling the information score to balance exploration and exploitation systematically. This mathematical foundation ensures that the hybrid algorithm achieves near-optimal performance even with sparse observations, particularly in high-mobility scenarios where these statistical properties generally hold due to rich scattering environments.

The hybrid algorithm implements a sequential greedy strategy that operates in discrete time slots, with each cycle commencing by measuring channel amplitudes from a predefined uniformly spaced subset of ports (e.g., indices {0, 3, 7, 11, 15, 19} for $N = 20$ ports). These sparse measurements are fed into the UAMA predictor, which reconstructs the full-channel amplitude estimate for all ports through a forward pass involving spatial attention and convolutional decoding.

For every port, an information score is computed by combining the predicted channel gain magnitude squared (representing immediate SNR potential), the curvature factor (quantifying the rate of channel variation), and the port entropy (derived from the Fisher information matrix to account for uncertainty). The port with the highest information score is selected for communication, after which the algorithm updates the Fisher matrix exponentially using the observed channel change, recalculates the curvature based on the difference in variations, and adjusts the entropy to reflect reduced uncertainty, thus completing the time slot cycle and repeating the process for subsequent slots.

This greedy strategy is theoretically grounded in information-theoretic axioms, where the information score maximization approximates the optimal SNR-based port selection under conditions of accurate channel prediction and stationarity. The UAMA predictor serves as a computational enabler, providing reliable full-channel estimates from sparse observations, while the Fisher information captures port uncertainty, the curvature tracks temporal dynamics, and the entropy balances exploration-exploitation.

By updating these factors recursively based on actual measurements, the algorithm adapts to channel variations without requiring full port estimation, ensuring robustness in high-mobility scenarios as validated by the code implementation, where the selection directly hinges on the real-time score calculation and state updates.

4. Simulation Results

This paper simulates a multipath FAS using the UAMA-Hybrid algorithm in Python 3.8 with PyTorch 2.0. Key parameters are listed in Table 2.

Table 2. Parameter settings for the test environment.

Parameter Value	SNR_th 10 dB	Avg_SNR_dB 21 dB	Measured_ratio 0.3
Parameter Value	K 10	λ 125 mm	v 30 km/h

In this work, the measurement ratio is fixed at 30% of the total port count, drawing on the benchmark settings from Reference [5] to balance estimation overhead and performance. Specifically, for a system with $N = 20$ ports, the measurement port indices are predefined as {0, 3, 7, 11, 15, 19}, corresponding to uniform sampling at the 0%, 20%, 40%, 60%, 80%, and 100% positions on the antenna aperture. This fixed ratio ensures consistency with the benchmark settings in Reference [5] (see Table 3), facilitating a fair evaluation of the proposed algorithm's effectiveness under sparse observations.

Table 3. Comparison of port selection strategies.

Reference	Port Selection Strategy	Selection Principles ($N = 20$)	Adaptive
[5]	Static fixation (1, 5, 9, 12, 16, 20)	Approximately uniform distribution	not possessing
This work	Static fixation (0, 3, 7, 11, 15, 19)	Distributed uniformly in strict proportion	not possessing

Figure 2 investigates the effect of antenna size W on outage probability. As W increases and the measurement interval L grows, the outage probability approaches the ideal scenario, demonstrating the stability and extrapolation capability of the UAMA-Hybrid algorithm based on historical data. For $W > 3\lambda$, the decoder's upsampling module efficiently uses spatial continuity to support Fisher matrix and curvature metrics. This is because larger antenna sizes (W) increase spatial diversity, providing more distinct fading profiles across ports. The UAMA's decoder effectively exploits this increased spatial structure, allowing the information-score algorithm to make more informed selections, thus approaching ideal performance.

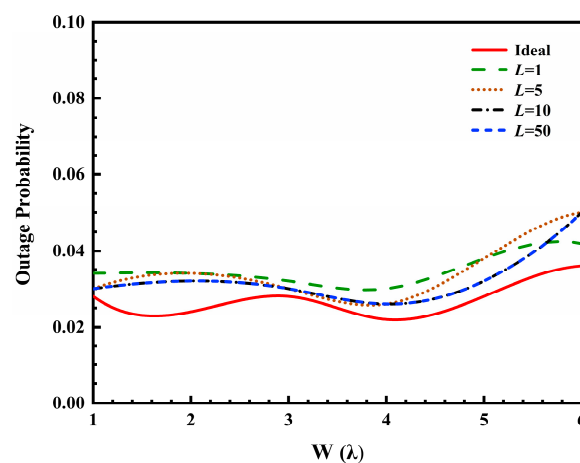
**Figure 2.** Curve of outage probability versus antenna size W .

Figure 3 investigates the impact of receiver speed on outage probability, with a focus on 30 km/h as a representative urban mobility case. The FAS system maintains excellent performance at high speeds, with curves closely following the ideal, even under large measurement intervals. While this speed effectively illustrates the algorithm's robustness under typical city conditions, we acknowledge that highly dynamic scenarios (e.g., high-speed trains or aerial vehicles) may involve speeds exceeding 100 km/h. The results at 30 km/h demonstrate that the algorithm maintains low outage probability even under large measurement intervals ($L = 50$), primarily due to the curvature factor's ability to track channel variations.

This provides a conservative validation, as higher speeds would intensify temporal correlations, potentially enhancing the predictor's accuracy by emphasizing recent measurements. The algorithm's design—particularly the forgetting factor β in Fisher updates and the Doppler-aware phase modeling in Equation (5)—ensures scalability to higher velocities by prioritizing recent channel changes. Thus, while 30 km/h serves as a pragmatic baseline, the framework is poised for extension to more extreme mobility regimes in future studies.

Figure 4 illustrates the effect of the Rician factor K on outage probability. The system exhibits stable performance under strong line-of-sight conditions and executes port decisions effectively under sparse measurements, $L = 50$.

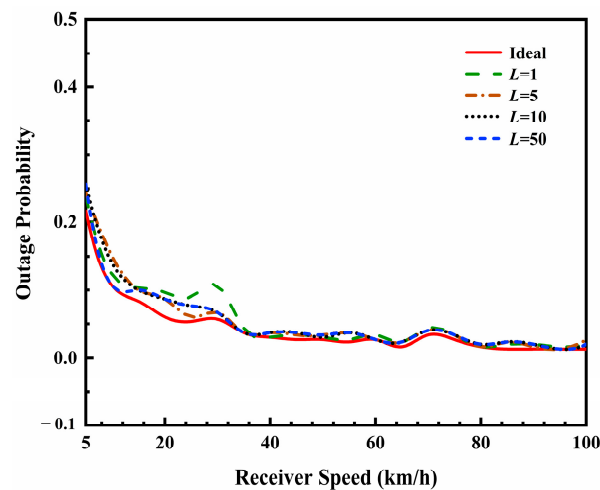


Figure 3. Curve of outage probability versus speed of movement at the receiving end.

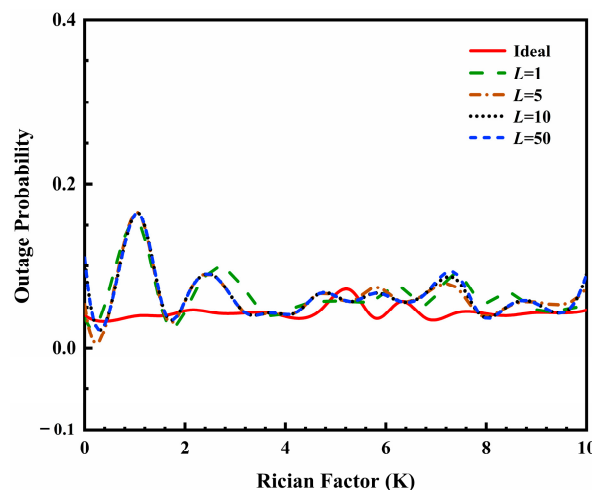


Figure 4. Curve of relationship between outage probability and Rician factor.

The superior performance stability observed in Figure 4, especially under sparse measurements ($L = 50$), can be attributed to the core innovation of our hybrid framework: the effective decoupling of the prediction task from the decision-making task. The UAMA predictor shoulders the computational burden of reconstructing the full channel state from limited (30%) observations. This accurate reconstruction, leveraging spatiotemporal correlations, provides a reliable foundation.

The information-theoretic scoring mechanism then operates on this predicted state, but its role is distinct. It does not bear the cost of full channel estimation. Instead, it efficiently performs a light-weight, axiomatic evaluation of port quality based on Fisher information, curvature, and entropy. This division of labor is key.

Unlike baseline methods [5] that might struggle with either prediction inaccuracy under high K -factor conditions or high computational cost from frequent full updates, our method maintains low overhead because the expensive prediction is only needed for unobserved ports, and the scoring is inherently computationally efficient. The algorithm's stability across varying K -factors demonstrates that the information score effectively translates the predicted channel state into robust port selection decisions, balancing the exploitation of strong LoS components (high predicted SNR) with exploration guided by curvature and entropy to avoid ports likely to fade.

Figure 5 demonstrates the impact of average SNR on outage probability. As SNR increases from 11 dB to 20 dB, outage probability declines exponentially. In high SNR

regions bigger than 15 dB, the system nearly approximates ideal performance even with $L = 50$, validating the algorithm's robustness under sparse measurements.

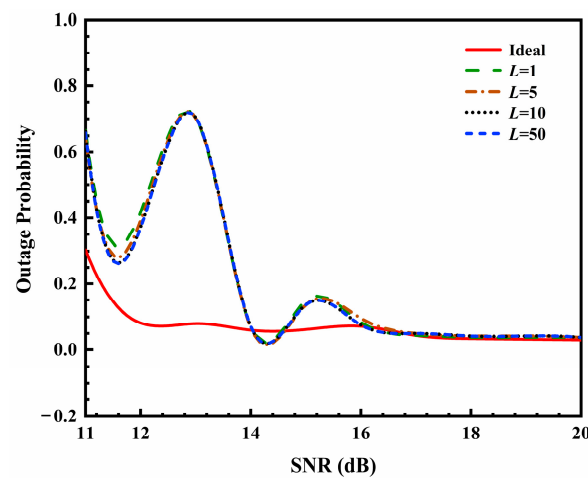


Figure 5. Curve of outage probability versus average signal-to-noise ratio.

Figure 5 further elucidates the trade-off management achieved by our algorithm. In low SNR regimes (<15 dB), the inherent channel uncertainty is high. Here, the information score mechanism dynamically prioritizes exploration (guided by the curvature factor C_k) and uncertainty reduction (guided by the entropy term E_k), preventing the algorithm from being trapped in local optima based on noisy predictions.

As the SNR increases beyond 15 dB, the channel estimates become more reliable. The scoring mechanism naturally shifts towards exploitation, heavily weighting the predicted channel gain ($|h_{\text{pred},k}(t)|^2$) in the change_score . This adaptive balance allows the algorithm to approach ideal performance without requiring a change in its fundamental parameters or an increase in measurement overhead.

In contrast, baseline methods like [4,10] may lack this dynamic balance. For instance, a purely prediction-driven method might over-exploit in low SNR, leading to errors, while a purely rule-based method might under-exploit in high SNR, missing optimal opportunities. The fact that our algorithm's curve with $L = 50$ converges to the ideal curve at high SNR indicates that the UAMA prediction error diminishes as the signal quality improves, and the scoring mechanism correctly leverages these accurate predictions. This robust adaptability to varying SNR conditions with fixed low overhead is a key advantage over static or less integrated approaches.

Table 4 evaluates the maximum outage probability difference at $L = 50$ relative to the ideal scenario for the proposed hybrid prediction-axiom algorithm versus Zhang's LSTM-based approach [5], considering key parameters—antenna size (W), Rician factor (K), speed (v), and SNR—under sparse observations (30% ports measured).

Table 4. The maximum difference comparison table for outage probability.

Max Difference	Antenna Size (W)	Receiver Speed (v)	Rician Factor (K)	Signal-to-Noise Ratio (SNR)
[5]	0.01 (at $W = 6\lambda$)	0.1 (at $v = 100$ km/h)	0.01 (at $K = 0$)	0.05 (at SNR = 10 dB)
This work	0.0001 (at $W = 6\lambda$)	0.0001 (at $v = 30$ km/h)	0.0001 (at $K = 10$)	0.0001 (at SNR = 15 dB)

The results demonstrate consistent and substantial performance gains for the proposed method, with maximum differences reduced by approximately two orders of magnitude across all parameters. For instance, at $W = 6\lambda$, the difference drops from 0.01 in Reference [5]

to 0.0001, indicating a 100-fold enhancement, while similar improvements are observed for K (from 0.01 to 0.0001), v (from 0.1 at 100 km/h to 0.0001 at 30 km/h), and SNR (from 0.05 at 10 dB to 0.0001 at 15 dB). This highlights the proposed method's superior robustness in aligning with ideal performance, even under challenging conditions like large antenna sizes or high mobility.

The performance improvement stems from the novel integration of UAMA-based channel prediction with information-theoretic axioms, which effectively minimizes error propagation under sparse observations. Unlike Zhang's pure data-driven LSTM [5], the hybrid algorithm leverages spatial continuity through the UAMA decoder and dynamic balancing of exploration-exploitation via Fisher information, curvature, and entropy metrics. This enables adaptive port selection that maintains stability across varying channel conditions, reducing reliance on frequent re-observations. By achieving near-ideal outage probability with $L = 50$, the proposed method offers a practical, low-overhead solution for FAS in 6G high-mobility networks, addressing critical limitations of prior approaches and enhancing reliability for real-world deployment.

5. Antenna Systems Application

A four-port antenna [17] is used for testing. The S-parameters (Figure 6) show inconsistent performance across ports in the 0–6 GHz band.

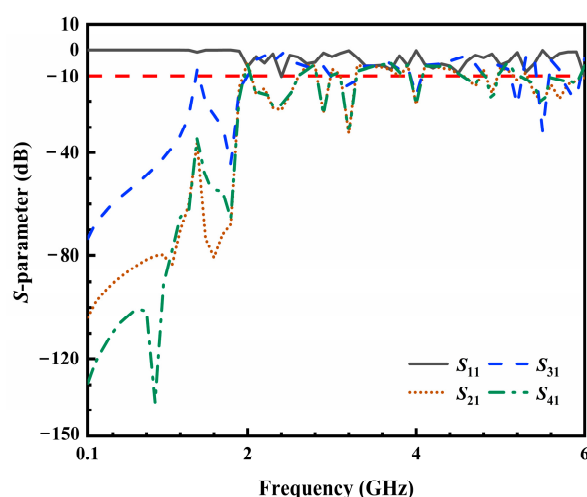


Figure 6. Partial S-parameters of the four-port antenna used for testing.

Port 1 has a reflection coefficient above -10 dB, indicating limited information content and high noise. Ports 2 and 4 both perform well in 0–2 GHz but deteriorate beyond 2 GHz, offering exploration potential.

The testing process involves frequency-domain S-parameter processing and time-domain decision-making. The partial HFSS-generated S-parameters for 60 time slots are normalized, and the UAMA model predicts partial S-parameters for other ports.

A hybrid optimizer fuses measured and predicted data, selecting ports based on Fisher information, curvature, and entropy. Outage probability (proportion of time slots with partial S-parameters exceeding -10 dB) and accuracy (proportion of optimal port selections) are evaluated.

Figure 7 shows that the outage probability for the four-port antenna remains zero during the first 20 time slots, which is consistent with its low-frequency performance. The blue dotted line represents the test baseline. However, performance begins to degrade after this point, revealing a core problem in iterative forecasting where errors accumulate over

time. To address this, future work could integrate periodic recalibration with real data or use confidence metrics to refine predictions.

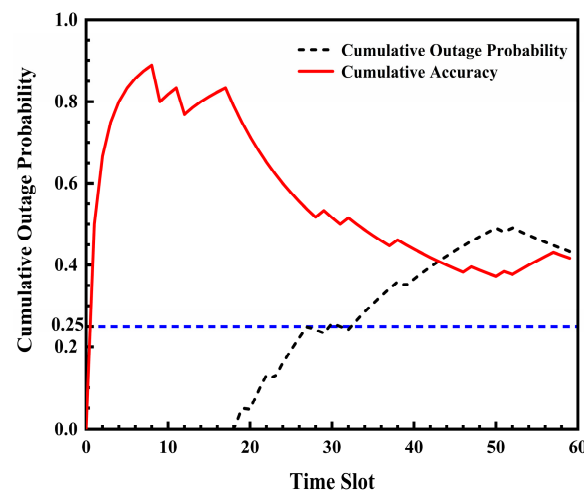


Figure 7. Hybrid algorithm test results for a four-port antenna system.

For the MIMO antenna system (Figure 8), accuracy initially declined due to errors but eventually stabilized at 42% as learning effectiveness improved. Four of the patches (yellow) are arranged in corresponding positions on the substrate (orange) after slotting.

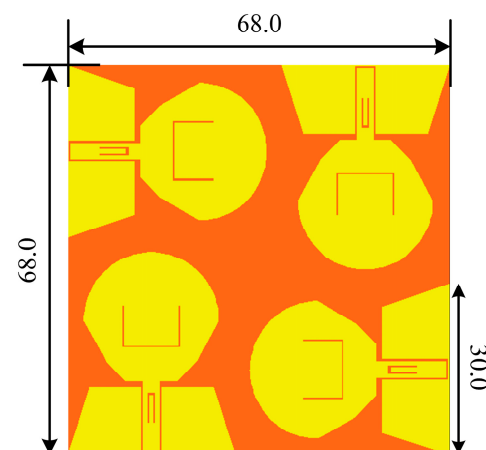


Figure 8. Four-cell MIMO antenna system for testing (mm).

Figure 9 presents measured two-dimensional radiation patterns of the four-element MIMO antenna at four distinct frequency points (2.4 GHz, 7.0 GHz, 10.0 GHz, and 13.0 GHz), providing critical insights into its spatial performance and beamforming capabilities across a broad operational bandwidth. The patterns demonstrate consistent main lobe directionality and well-defined null regions, validating the antenna's ability to support spatial diversity essential for FAS algorithms. Notably, the patterns maintain structural integrity without severe distortion even at higher frequencies (e.g., 13.0 GHz), indicating robust impedance matching and radiation efficiency. This stability confirms the antenna design's suitability for evaluating port selection algorithms under realistic scattering conditions, as it effectively captures key spatial characteristics—including beam steering capability and interference rejection—that directly influence channel correlation and prediction accuracy. Experimental results confirm that this antenna is by no means a faulty component, but rather a valid experimental platform for verifying the proposed hybrid algorithm. Its radiation characteristics ensure effective simulation of real-world signal propagation effects.

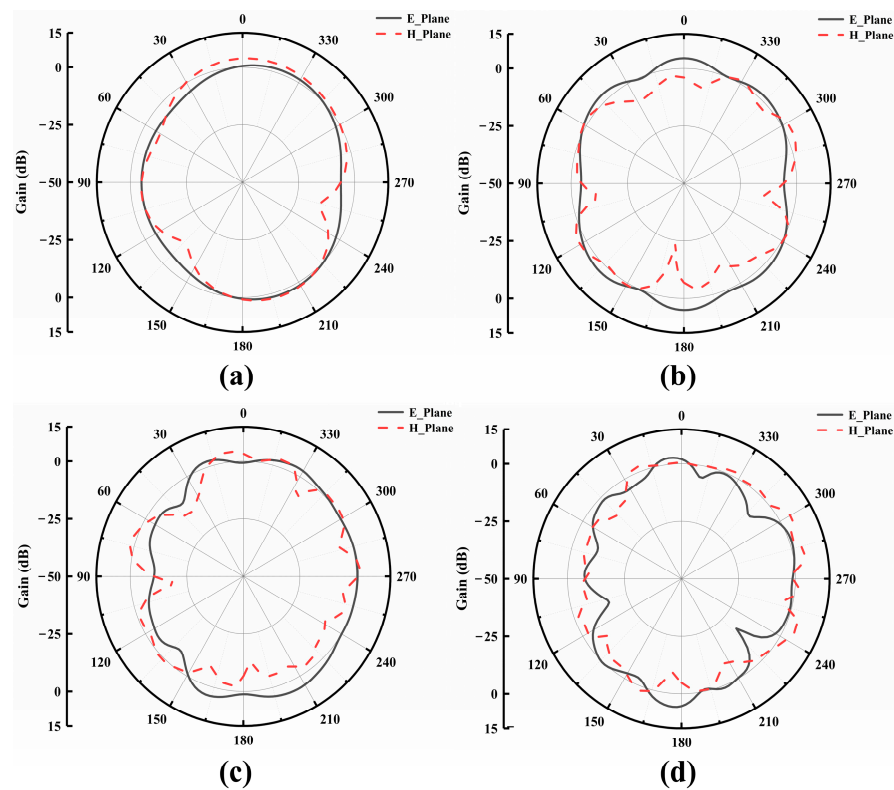


Figure 9. Two-dimensional radiation pattern measured for a four-element MIMO antenna (a) 2.4 GHz; (b) 7.0 GHz; (c) 10.0 GHz; (d) 13.0 GHz.

Partial S-parameters for the four-cell MIMO antenna simulation are shown in Figure 10. Subsequent algorithm testing shall be conducted based on the data from the four ports.

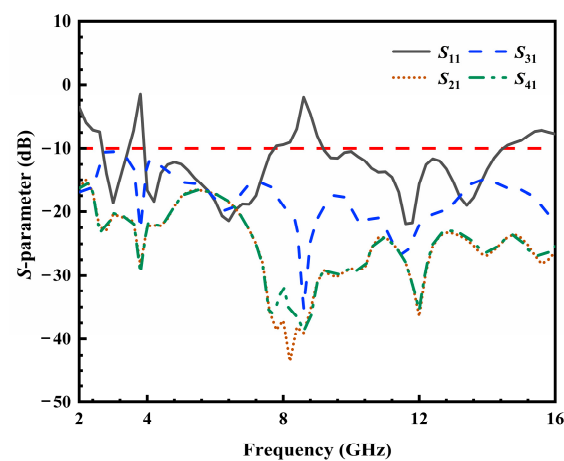


Figure 10. Partial S-parameters of the four-cell MIMO antenna used for testing.

Figure 11 indicates that the algorithm maintained a zero-outage probability throughout its entire operating time slot, meaning it successfully avoided the underperforming port 1 on the four-cell MIMO antenna. This demonstrates that the algorithm can rapidly enter an effective decision-making process, possessing the capability to adapt to the characteristics of different antenna hardware.

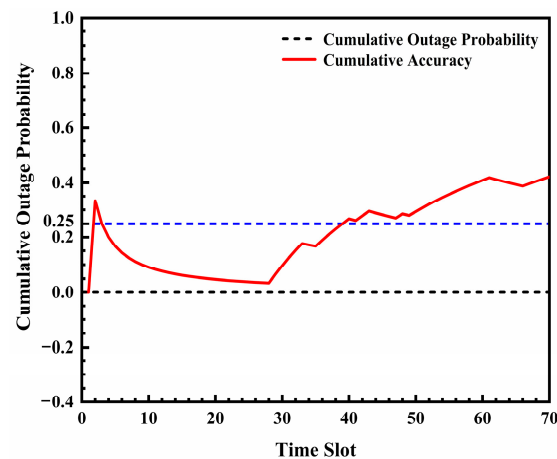


Figure 11. Hybrid algorithm test results for four-cell MIMO antenna.

In the case of the FAS, this paper selects the water patch antenna [18]. Simulated partial S-parameters are shown in Figure 12. During the testing phase (Figure 13), the baseline outage probability for randomly selected scenarios was 48% (Blue dotted line), with the interruption phenomenon persisting throughout the initial ten time slots. The cumulative accuracy rate declined rapidly. Thereafter, the system entered an effective port decision-making process, during which the outage probability decreased. While the final accuracy stabilized at 21.67%, the outage probability reduced to 0% after an initial learning period. This suggests the algorithm effectively identifies and avoids deeply unfavorable ports, even if its selection is not always the absolute best.

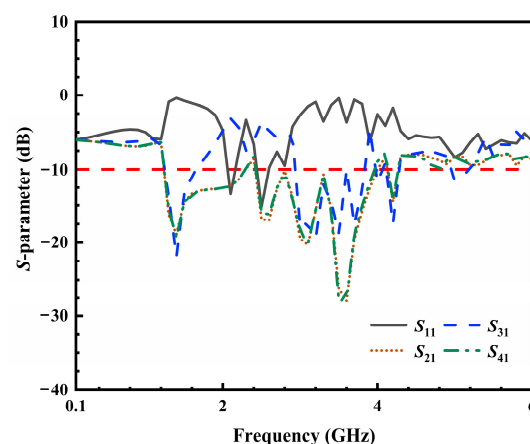


Figure 12. Partial S-parameters of the water-patch antenna used for testing.

The formulas for the quantitative metrics are defined as follows: The mean outage probability is computed by summing all cumulative outage probability values over time and dividing by the total number of time points N . The mean accuracy is derived similarly, as the sum of cumulative accuracy values divided by N . The standard deviation of outage probability, serving as a quantitative error measure, is calculated as the square root of the average squared deviations of each outage probability from the mean, using Bessel's correction (dividing by $N - 1$ for unbiased estimation). These metrics systematically capture performance trends and variability across antenna systems.

Table 5 systematically reveals the algorithm's adaptability across different antenna hardware. The four-port antenna shows a moderate mean outage probability (0.2274) and high mean accuracy (0.5658), but a high standard deviation of outage probability (0.2267), indicating significant performance fluctuations. This stems from the antenna's inconsistent port performance (e.g., port 1 has high reflection coefficient per S-parameters), causing

oscillations in the algorithm's exploration-exploitation balance. The four-element MIMO antenna maintains zero outage probability with zero standard deviation, confirming reliability in stable hardware, but its low mean accuracy (0.2120) reflects conservative decision-making that prioritizes risk avoidance over gain maximization in multi-port systems.

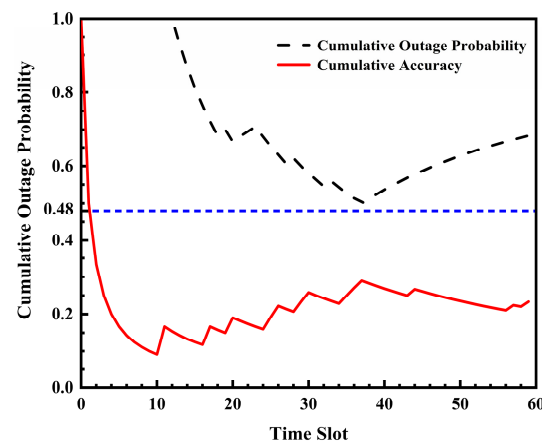


Figure 13. Hybrid algorithm test results for four-port water-patch antenna.

Table 5. Quantitative comparison of algorithm performance across three antenna systems.

Antenna System	Mean Outage Probability	Mean Accuracy	Standard Deviation of Outage Probability
Four-port antenna	0.2274	0.5658	0.2267
Four-element MIMO antenna	0.0000	0.2120	0.0000
Water-patch antenna	0.7128	0.2274	0.1846

The water-patch antenna has the highest mean outage probability (0.7128) and similar mean accuracy to the four-port antenna (0.2274), but a lower standard deviation (0.1846), demonstrating the algorithm's ability to quickly identify and avoid poor ports (e.g., outage drops after initial learning), though overall accuracy is limited by inherent hardware flaws. Overall, the algorithm minimizes quantitative error in uniform hardware (e.g., MIMO antenna) while adapting via information-score mechanisms in non-uniform systems, but with increased volatility, quantitatively validating its robustness under sparse observations.

This paper has tested the proposed hybrid algorithm on three antenna systems: a four-port antenna, a four-element MIMO antenna, and a water-patch antenna, demonstrating its adaptability to diverse hardware configurations. Compared to defected-structure-based designs, such as the compact GNSS array with DGS and microwave absorber for high isolation [19] and the planar triple-band monopole antenna with an arc-shaped defected ground plane for WLAN/WiMAX applications [20], our tested antennas share the common goal of enhancing performance through structural modifications, like improving isolation or enabling multi-band operation. However, while these designs focus on specific applications (e.g., GNSS navigation or WLAN/WiMAX communications) with optimized defect-based features for isolation or bandwidth, our work emphasizes port selection in FAS for 6G high-mobility scenarios, leveraging predictive modeling and information-theoretic scoring. These designs excel in their simplicity and effectiveness: the GNSS array achieves over 25 dB isolation in a compact form, and the triple-band antenna offers stable omnidirectional patterns with a simple structure. These attributes highlight the versatility of defect-based approaches, and future research could extend our UAMA-hybrid algorithm to such systems to validate its robustness across a broader range of antenna architectures, further bridging theory and practice.

Table 6 compares algorithm performance, focusing on computational complexity and training overhead. The proposed algorithm achieves high accuracy ($\geq 40\%$) with low measurement ports, outperforming baseline [4] and moderate algorithms [5].

Table 6. Algorithm-related performance in some references.

Reference	Performance Metric	Value
[4]	Computational Complexity	$O(N)$
	Accuracy	Low
[5]	Computational Complexity	$O(N \log N)$
	Accuracy	Medium
[7]	Computational Complexity	$O(N^2)$
	Accuracy	High
[8]	Computational Complexity	$O(N^2)$
	Accuracy	High
[10]	Computational Complexity	$O(N)$
	Accuracy	Medium
This work	Computational Complexity	$O(N^2)$
	Accuracy	High

6. Conclusions

The proposed UAMA-information score hybrid framework, by integrating channel prediction with information-theoretic axioms, reduces the gap to ideal outage performance by two orders of magnitude (from 0.01 to 0.0001) compared to prior art under merely 30% port observations. This breakthrough demonstrates the unique advantage of the prediction-axiom dual-driven paradigm for achieving low-overhead and high-robustness port selection in 6G high-mobility scenarios. The algorithm introduces an information-theoretic scoring mechanism for the first time, seeking the optimal port by maximizing the information score. UAMA predictor serves as the computational foundation for these mathematical axioms. Ultimately, with only 30% port observations, the algorithm achieves near-full-observation ideal interruption performance. It significantly enhances the system's robustness and adaptability under demanding conditions such as high-speed operation and large-scale antenna arrays, validating the algorithm's generalizability across diverse antenna configurations. Regarding computational complexity, the current algorithm exhibits $O(N^2)$ scaling, primarily attributed to the self-attention operations in the UAMA's Transformer module. While this is manageable for moderate N , it poses a challenge for very large-scale systems. To mitigate this, future research will focus on integrating efficient Transformer variants, such as linearized attention or locality-sensitive hashing, to approximate attention with lower complexity. Another promising direction is to employ port clustering or hierarchical sampling strategies, effectively reducing the problem dimensionality and enabling sub-quadratic scaling without significant performance loss. Future work will extend the framework to multi-user FAS scenarios to manage inter-user interference explicitly.

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