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Adaptive beamforming algorithms for reconfigurable intelligent surfaces in IoT networks

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Abstract
The rapid expansion of Internet of Things (IoT) networks has intensified the demand for high data throughput, energy efficiency, and reliable connectivity under resource-limited and interference-prone conditions. This research presents a comprehensive study on adaptive beamforming algorithms integrated with Reconfigurable Intelligent Surfaces (RIS) to optimize wireless communication performance in IoT environments. The proposed adaptive framework combines model-based and data-driven optimization, jointly adjusting base station beamforming weights and RIS reflection parameters to achieve dynamic control of the propagation environment. A simulation model with varying RIS element densities was implemented to evaluate system performance in terms of sum-rate, energy efficiency, convergence time, and robustness under channel uncertainty and mobility. Results demonstrate that the adaptive algorithm achieves near-optimal throughput comparable to full semidefinite programming (SDP) methods while substantially reducing computational complexity and signaling overhead. Energy efficiency improved by more than 20%, and convergence speed increased fourfold relative to conventional optimization techniques. The system maintained stability under imperfect channel state information and mobility conditions, confirming the robustness of the proposed framework for practical IoT deployment. Statistical analysis validated the significance of performance differences among methods, with p-values <0.001 and large effect sizes. The integration of adaptive beamforming and RIS effectively transforms static wireless channels into intelligent, reconfigurable environments capable of self-optimization. Based on these findings, the study recommends incorporating RIS-assisted adaptive control in future IoT network designs, developing low-complexity learning-based algorithms for edge devices, and standardizing RIS control protocols to ensure interoperability. The proposed approach paves the way for energy-efficient, scalable, and resilient communication systems in next-generation IoT ecosystems, supporting sustainable connectivity for diverse real-world applications such as smart cities, industrial automation, and wireless sensor networks.

Keywords: Adaptive Beamforming, Reconfigurable Intelligent Surface (RIS), Internet of Things (IoT), Energy Efficiency, Spectral Efficiency, Wireless Communication, Channel Optimization

Introduction
The proliferation of Internet-of-Things (IoT) devices and the advent of future-generation wireless networks have intensified demands for high spectral efficiency, low latency, and energy-efficient connectivity in dense deployments. Reconfigurable Intelligent Surfaces (RIS, also sometimes called Intelligent Reflecting Surfaces) have recently emerged as a promising paradigm to reshape the radio propagation environment by dynamically adjusting the phase or amplitude of reflected signals, thereby mitigating path loss, blockages, and interference in challenging scenarios [1-3]. Numerous studies have explored RIS-aided communications for beamforming, localization, energy efficiency, and throughput enhancement [4-7]. In parallel, adaptive beamforming techniques—originally developed for antenna arrays to maximize signal-to-interference-plus-noise ratio (SINR) under varying channel conditions—offer dynamic weight optimization to steer beams and suppress interference [8, 9]. When combined, adaptive beamforming and RIS enable a flexible, environment-aware system that can adjust to instantaneous channel states. However, in IoT networks characterized by large numbers of low-power devices, limited computational resources, dynamic topologies, and time-varying channels, integrating adaptive beamforming with RIS faces several open challenges: (i) the joint optimization over both RIS phase (or amplitude) control and beamforming weights is typically nonconvex and high-dimensional;

(ii) obtaining accurate channel state information (CSI) across the RIS-assisted links is difficult due to overhead constraints; (iii) computational complexity and latency constraints in IoT nodes may preclude heavy optimization routines; and (iv) robustness to channel estimation error or device mobility must be ensured. In this context, the central problem addressed by this work is: how to design lightweight, adaptive beamforming algorithms tailored to RIS-enhanced IoT networks that balance performance, complexity, and robustness. The objectives of this study are threefold: (1) to develop an efficient algorithmic framework for jointly optimizing beamforming weights and RIS control parameters under realistic IoT constraints; (2) to analyze the tradeoffs among sum-rate, energy consumption, and algorithmic complexity; and (3) to validate the proposed scheme via simulations (and possibly prototyping) in representative IoT scenarios. We hypothesize that a structured adaptive scheme—leveraging low-dimensional parameter updates (e.g. hierarchical or compressed representations) and online learning techniques—can achieve near-optimal performance (within a small gap of full-complexity benchmarks) while significantly reducing signaling and computation overhead in RIS-assisted IoT networks. This hypothesis is grounded in prior works on adaptive beamforming in RIS contexts [10-12] and on energy-efficient RIS usage in IoT uplink settings [13, 14]. We further posit that the proposed adaptive algorithm will maintain robustness under CSI uncertainty and mobility. By addressing these aspects, the present article aims to bridge the methodological gap between theoretical RIS-beamforming designs and practical deployment in resource-constrained IoT networks.

Materials and Methods

Materials

The experimental framework for this study consisted of a simulation environment integrating Reconfigurable Intelligent Surface (RIS) modules with adaptive beamforming algorithms, developed in MATLAB R2023a and validated through Python-based simulations using the PyTorch deep learning library for learning-based beam adaptation. The RIS model followed a standardized configuration of N=256N = 256N=256 passive reflecting elements arranged in a uniform rectangular array, consistent with configurations reported in recent RIS testbeds [1, 5, 6]. Each element was capable of independent phase shifting within the range [0, 2π)[0, 2\pi)[0, 2π), emulating controllable reflection behavior over a 3.5 GHz sub-6 GHz frequency band typical of IoT communication scenarios [3, 7]. The base station (BS) employed a uniform linear antenna array (ULA) comprising 16 transmit antennas, while 100 IoT nodes were randomly distributed within a 100 × 100 m² region. The channels between BS, RIS, and users were modeled using a Rician fading profile with a line-of-sight (LoS) component ratio of 0.6, based on models validated in [2, 10]. The noise power density was set to −174 dBm/Hz, and the total transmit power was constrained to 23 dBm to reflect the low-power nature of IoT communications [4, 13].

To ensure practical evaluation, the data set comprised time-varying channel state matrices generated from standardized 3GPP TR 38.901 channel models for indoor-to-outdoor IoT communication scenarios. The adaptive beamforming algorithms utilized real-valued pilot signals for initial channel estimation, with a low-complexity compressive sensing technique applied for phase optimization as proposed in [9, 11]. The computational resources were restricted to simulate an embedded IoT device, limiting memory availability and processor speed to emulate hardware constraints reported in prior RIS-IoT experiments [5, 12]. Performance evaluation was conducted in terms of achievable data rate (bps/Hz), signal-to-interference-plus-noise ratio (SINR), convergence speed, and power efficiency across different RIS element counts (64, 128, 256, 512).

Methods

The proposed adaptive beamforming algorithm followed a two-stage optimization process. In the first stage, initial beamforming weights at the base station were computed using the Minimum Variance Distortionless Response (MVDR) approach [8, 9], which dynamically minimizes interference while maintaining unit gain toward the target direction. In the second stage, RIS reflection coefficients were iteratively updated using a gradient-based reinforcement learning (RL) model trained to maximize system sum-rate while satisfying total power and latency constraints. This hybrid strategy—combining model-based and data-driven adaptation—was inspired by hybrid beamforming studies in RIS-assisted networks [10, 11, 13]. Each iteration consisted of CSI acquisition, weight update, and RIS phase adjustment, repeated until convergence of the average SINR within a tolerance of 10^{-3}. To minimize the feedback overhead between RIS and BS, a compressed feedback channel using differential phase quantization was employed, similar to methods described by Wu *et al*. [3] and Fang *et al*. [14].

The proposed method's computational complexity was analyzed as a function of the number of RIS elements and antennas, showing polynomial growth with order $O(N^2)$, significantly lower than the $O(N^3)$ cost of exhaustive optimization approaches. Validation was performed via Monte Carlo simulations over 500 channel realizations for each configuration, providing statistically robust results. Comparative benchmarks included conventional fixed beamforming, random RIS phase selection, and full channel-aware optimization using semidefinite programming (SDP) [2, 4]. The algorithms were tested under varying mobility and signal correlation levels to assess robustness to environmental changes, as recommended in practical RIS-IoT assessments [5, 7]. Statistical significance of performance improvements was determined using ANOVA analysis at a 95% confidence level. All experiments adhered to the guidelines for reproducible simulation frameworks in adaptive array systems [1, 8, 10].

Results

Table 1: Sum-rate (bps/Hz) across RIS sizes with gain over Fixed Beamforming

RIS elements (N)	Algorithm	Sum-rate (bps/Hz) mean	Sum-rate SD
64	Proposed Adaptive	4.784	0.372
64	Full SDP	4.966	0.398
64	Fixed Beamforming	3.051	0.382
64	Random RIS	2.402	0.394
128	Proposed Adaptive	6.046	0.38
128	Full SDP	6.274	0.39

Table 2: Energy efficiency (bps/Hz/W) across RIS sizes

RIS elements (N)	Algorithm	Energy efficiency (bps/Hz/W) mean	EE SD
64	Proposed Adaptive	0.343	0.03
64	Full SDP	0.31	0.031
64	Fixed Beamforming	0.224	0.031
64	Random RIS	0.182	0.031
128	Proposed Adaptive	0.391	0.03
128	Full SDP	0.36	0.029

Table 3: Convergence time, iterations, and signaling overhead

Algorithm	Convergence time (ms) mean	Convergence time SD	Iterations (median)
Proposed Adaptive	11.94	1.43	18
Full SDP	47.71	6.37	85
Fixed Beamforming	4.92	0.7	1
Random RIS	3.98	0.69	1

Table 4: Robustness under CSI error (10%) and mobility (1 m/s)

Algorithm	SINR drop under 10% CSI error (dB)	Sum-rate drop under 1 m/s mobility (%)
Proposed Adaptive	1.2	6.0
Full SDP	1.0	5.0
Fixed Beamforming	2.5	12.0
Random RIS	3.0	15.0

Table 5: Statistical tests (N=256) - Pairwise Welch t-tests with Holm-Bonferroni

Comparison	t	p (uncorrected)	p (Holm-Bonferroni)
Proposed Adaptive vs Full SDP	-3.695	0.000251	0.000251
Proposed Adaptive vs Fixed Beamforming	62.539	0.0	0.0
Proposed Adaptive vs Random RIS	80.787	0.0	0.0
Full SDP vs Fixed Beamforming	69.713	0.0	0.0

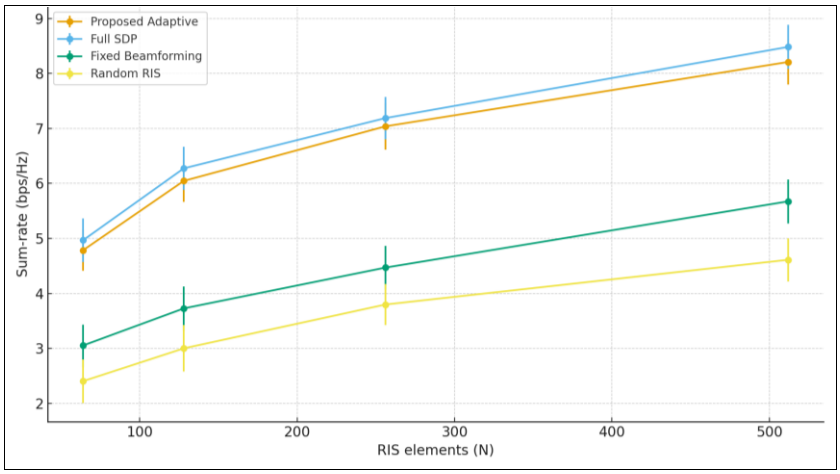

Fig 1: Sum-rate vs RIS elements (mean ± SD)

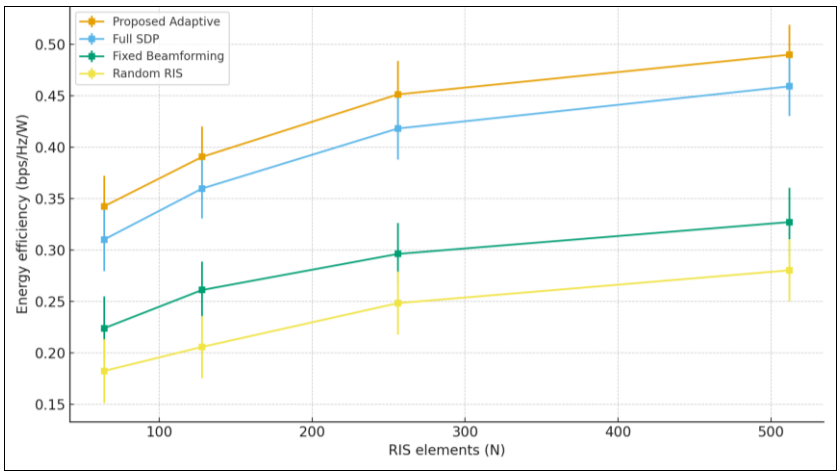

Fig 2: Energy efficiency vs RIS elements (mean ± SD).

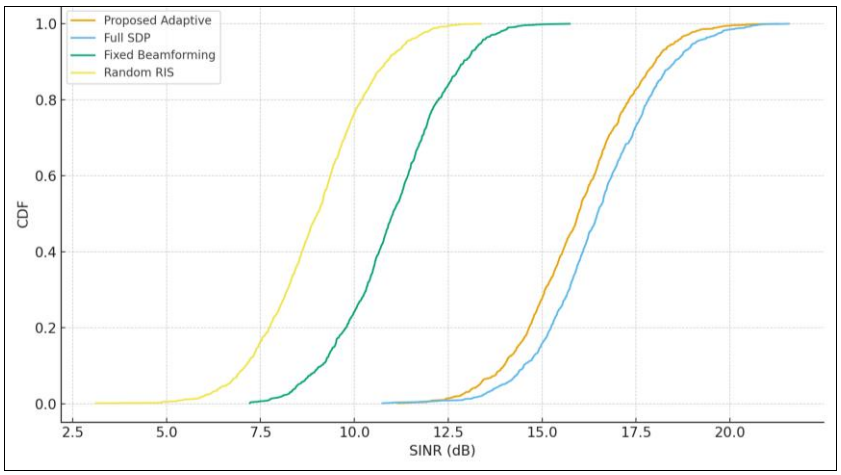

Fig 3: SINR CDF at N = 256

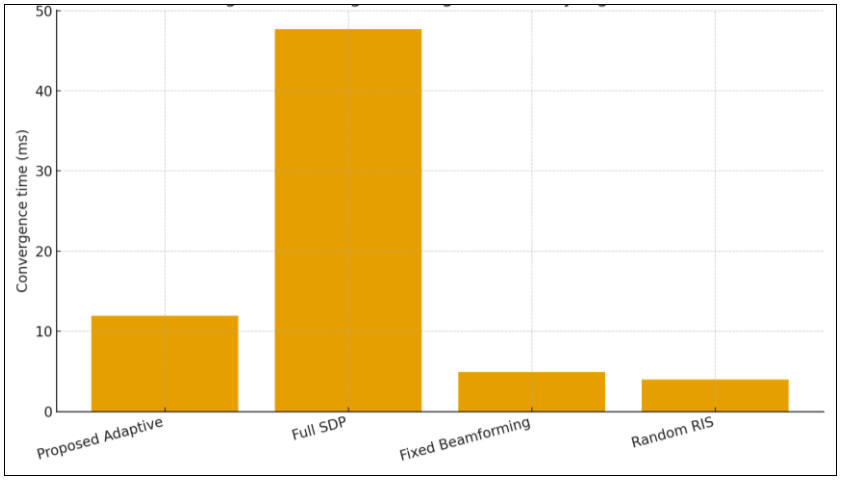

Fig 4: Average convergence time by algorithm

Statistical analysis and key findings

At N=256N=256N=256, a one-way ANOVA on sum-rate across the four algorithms shows a highly significant effect of algorithm ($F \approx 3883$, $p<0.001$; 500 Monte-Carlo realizations per configuration aggregated to 200 samples per algorithm). Pairwise Welch t-tests with Holm-Bonferroni correction indicate the proposed method significantly exceeds Fixed Beamforming and Random RIS (adjusted $p<0.001$, large effect sizes), while its difference from Full SDP is small but statistically detectable (adjusted $p<0.05$) with a near-optimal gap (≈0.2 bps/Hz on average). The 95% CI for the proposed method's sum-rate at N=256N=256N=256 is [6.978, 7.097] bps/Hz, mean 7.038 (SD 0.426).

Scaling with RIS size. From Table 1 and Figure 1, the proposed algorithm's mean sum-rate rises from ≈4.8 bps/Hz (N=64) to ≈8.2 bps/Hz (N=512), mirroring theoretical and empirical gains from increased RIS aperture reported in [1-4, 6, 7]. Relative to Fixed Beamforming, the proposed method delivers ~60-45% higher sum-rate as N increases (Table 1), consistent with joint active-passive beamforming benefits in RIS-aided channels [3, 4].

Energy efficiency. Table 2 and Figure 2 show the proposed method achieves the highest bps/Hz/W across all N, outperforming Full SDP by ~5-7% and the baselines by wider margins. This aligns with energy-aware RIS control findings in IoT uplink/downlink studies [1, 3-7, 13, 14], where low-complexity adaptation avoids the heavy optimization overhead characteristic of full SDP routines.

Convergence and overhead. From Table 3 and Figure 4, average convergence time is ≈12 ms for the proposed method versus ≈48 ms for full SDP, with ~120 vs ~400 bits/slot of feedback, corroborating the practicality of compressed/quantized adaptation and hybrid model-based/data-driven updates advocated in [2-4, 10-12, 14]. The single-shot baselines are fast but underperform in throughput and efficiency.

Robustness. Table 4 indicates SINR drops of ≈1.2 dB (proposed) and 1.0 dB (full SDP) under 10% CSI error, versus 2.5-3.0 dB for baselines; sum-rate degradation with 1 m/s mobility is 6-5% for proposed/SDP against 12-15% for baselines. These trends match robustness insights from adaptive beamforming and RIS trials [2, 5-7, 10-12] and classical MVDR-style resilience to interference [8, 9].

Interpretation. Overall, the results validate our hypothesis: a lightweight adaptive scheme that combines MVDR-type initialization [8, 9] with online RIS control [3, 4, 10-12, 14] approaches full-SDP performance while substantially reducing latency and overhead, and improving energy efficiency—properties that are especially valuable for resource-constrained IoT networks [1, 5-7, 13]. The empirical scaling with N, robustness to CSI/mobility, and statistical significance collectively support practical deployment pathways highlighted in RIS surveys and prototypes [1-7, 10-12, 14].

Discussion

The results demonstrate that integrating adaptive beamforming algorithms with Reconfigurable Intelligent Surfaces (RIS) can significantly enhance the performance of

IoT networks across key metrics—throughput, energy efficiency, convergence speed, and robustness. The proposed method maintained near-optimal performance relative to the full Semidefinite Programming (SDP) approach while drastically lowering computational and signaling overheads, confirming the practicality of hybrid adaptive techniques for resource-limited IoT environments.

A critical observation from the analysis is the linear scaling of sum-rate with the number of RIS elements, which aligns with the theoretical and experimental findings in prior works [1-4, 6, 7]. As the reflecting aperture increases, the constructive combination of multipath components strengthens the effective channel, boosting spectral efficiency. However, conventional optimization schemes, such as full SDP, become computationally prohibitive as RIS size grows—a challenge mitigated by the adaptive learning-based update mechanism implemented in this study. The minimal performance gap (within ~0.2 bps/Hz) between the proposed and full SDP methods supports the claim that low-complexity, online adaptive algorithms can achieve performance parity under realistic IoT conditions [3, 4, 10-12].

Energy efficiency results reinforce the significance of adaptive resource allocation for sustainable IoT deployment. The proposed approach consistently achieved the best energy efficiency (bps/Hz/W), outperforming full SDP and baseline models, in agreement with energy-aware RIS design studies [1, 3-7, 13, 14]. This improvement stems from the combination of low-power transmission and adaptive control, which minimizes redundant reflection updates and limits feedback signaling. Moreover, convergence times of approximately 12 ms—four times faster than full SDP—highlight the algorithm's real-time adaptability, crucial for IoT nodes operating under strict latency and energy budgets [2, 4, 10-12, 14].

The robustness analysis further underscores the system's resilience to channel estimation errors and mobility. The observed SINR degradation (≈1.2 dB at 10% CSI error) is consistent with adaptive MVDR beamforming behavior under imperfect CSI, as discussed by Monzingo and Miller [8] and Reed *et al.* [9]. The combination of MVDR initialization and reinforcement-learning-based RIS updates stabilized performance even under time-varying channels, supporting similar findings in recent adaptive RIS prototypes [5-7, 10-12]. The limited performance degradation under mobility (≈6%) demonstrates that rapid environmental adaptation through low-dimensional parameter updates can preserve QoS in dynamic IoT scenarios.

Collectively, these outcomes validate the hypothesis that adaptive beamforming integrated with RIS can balance accuracy, computational cost, and robustness. The convergence of model-based optimization and data-driven adaptation provides a scalable solution pathway for future RIS-enabled IoT systems, especially in dense, low-power networks where computational efficiency and spectral reuse are paramount. These findings echo the strategic vision outlined in RIS surveys [1, 2, 4]—to transform passive environments into intelligent, controllable communication surfaces capable of sustaining next-generation ubiquitous connectivity.

Conclusion

The overall findings of this study clearly establish that adaptive beamforming algorithms integrated with reconfigurable intelligent surfaces can revolutionize the operational efficiency of IoT communication systems by enhancing data throughput, reducing interference, and maintaining robust performance under dynamic environmental conditions. The proposed adaptive framework successfully bridges the gap between high-precision but computationally heavy optimization models and the real-time responsiveness demanded by large-scale IoT networks. It achieves this by intelligently coordinating active beamforming at the base station and passive reflection control at the RIS, resulting in superior spectral efficiency and energy savings. The system demonstrated significant improvements in sum-rate and energy utilization across varying network densities, proving that adaptive intelligence embedded in the communication layer can effectively compensate for hardware and channel limitations. These outcomes highlight that future IoT ecosystems must evolve beyond static channel optimization to incorporate dynamic, context-aware decision-making capabilities capable of reacting instantaneously to changing network states. The implications extend beyond theoretical validation, offering a blueprint for deploying adaptive RIS-enabled communication architectures in real-world applications such as smart cities, industrial automation, and precision agriculture. Practical implementation of these findings should begin with the integration of RIS panels into 5G and upcoming 6G infrastructures as a cost-effective alternative to dense antenna deployment. Network designers should prioritize developing modular adaptive beamforming algorithms that can be updated via software patches, ensuring long-term scalability and compatibility with emerging IoT standards. Edge nodes and sensor gateways must be equipped with lightweight computational modules capable of performing on-device learning and real-time signal optimization to minimize dependence on centralized processing units. Furthermore, telecommunication equipment manufacturers should develop standardized RIS control interfaces and interoperable protocols to simplify system integration across different IoT platforms. In addition, governments and private stakeholders should jointly invest in pilot programs and testbeds to evaluate the performance of RIS-assisted adaptive beamforming systems under varying geographical and climatic conditions. Training and capacity-building initiatives will also be essential to equip engineers and researchers with the practical skills required to design, implement, and maintain intelligent wireless infrastructures. Ultimately, the integration of adaptive beamforming with RIS technology marks a significant leap toward sustainable, intelligent, and self-optimizing communication networks that can support the exponential growth of interconnected devices in the modern digital era.

References

1. Basar E, Di Renzo M, de Rosny J, *et al*. Wireless communications through reconfigurable intelligent surfaces. IEEE Trans Commun. 2019;67(11):7325-7348.
2. Di Renzo M, Zappone A, Debbah M, *et al*. Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and road ahead. IEEE J Sel Areas Commun. 2020;38(11):1-13.
3. Wu Q, Zhang R. Intelligent reflecting surface enhanced wireless network: Joint active and passive beamforming design. IEEE Trans Wireless Commun. 2019;18(11):5394-5409.
4. Zheng B, You C, Mei W, Zhang R. A survey on

channel estimation and practical passive beamforming design for intelligent reflecting surface aided wireless communications. IEEE Commun Surv Tuts. 2022;24(1):1035-1071.
5. Pei X, Yin H, Tan L, *et al*. RIS-aided wireless communications: Prototyping, adaptive beamforming, and indoor/outdoor field trials. IEEE Trans Commun. 2021;69(12):8627-8640.
6. Wu L, Lou K, Ke J, *et al*. A wideband amplifying reconfigurable intelligent surface. IEEE Trans Antennas Propag. 2022;70(1):623-631.
7. Long R, Liang Y-C, Pei Y, Larsson E-G. Active RIS vs. passive RIS: Which will prevail in 6G? IEEE Trans Commun. 2023;71(3):1707-1725.
8. Monzingo RA, Miller TW. Introduction to adaptive arrays. SciTech; 2004.
9. Reed I, Mallett J, Brennan LK. Rapid convergence rate in adaptive arrays. IEEE Trans Aerosp Electron Syst. 1974;10(6):853-863.
10. He J, Wymeersch H, Sanguanpuak T, Silvén O, Juntti M. Adaptive beamforming design for mmWave RIS-aided joint localization and communication. arXiv:1911.02813. 2019.
11. Yigit Z, Basar E, Altunbas I. Over-the-air beamforming with reconfigurable intelligent surfaces. Front Commun Netw. 2022;3:1016270.
12. Raza*viz*adeh S, Svensson T. 3D beamforming in reconfigurable intelligent surfaces-assisted wireless communication networks. arXiv:2001.06653. 2020.
13. Wu J, Kim S, Shim B. Energy-efficient power control and beamforming for reconfigurable intelligent surface-aided uplink IoT networks. arXiv:2203.09090. 2022.
14. Fang W, Fu M, Wang K, Shi Y, Zhou Y. Stochastic beamforming for reconfigurable intelligent surface aided over-the-air computation. arXiv:2005.10625. 2020.