Recent Advances in Artificial Intelligence for RIS in 6G Wireless Networks

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***Abstract*—Reconfigurable Intelligent Surfaces (RIS) are envisioned as a key enabler for sixth-generation (6G) wireless networks, offering dynamic control over the radio environment to improve coverage, capacity, and energy efficiency. However, optimizing RIS-assisted systems presents significant challenges due to high-dimensional configuration spaces and complex wireless propagation. Artificial Intelligence (AI) techniques have emerged as powerful tools to address these challenges. This survey provides a concise overview of AI-driven approaches for RIS in 6G, focusing on three core applications: (1) RIS configuration and beamforming, (2) RIS channel estimation, and (3) resource management in RIS-assisted networks. For each area, we highlight how learning-based methods – including supervised learning, deep reinforcement learning (DRL), federated learning (FL), and generative models – contribute to performance gains. Recent IEEE works are cited to exemplify state-of-the-art solutions. It conclude by identifying open research directions in applying AI to RIS-empowered 6G communications.**

***Index Terms*—AI, Reconfigurable Intelligent Surfaces (RIS), 6G.**

I. Introduction

Next-generation 6G wireless networks demand unprecedented capacity, reliability, and adaptability. Reconfigurable Intelligent Surfaces (RIS) planar metasurfaces with electronically tunable elements, have emerged as a promising technology to reconfigure wireless propagation environments, enabling smart radio environments in 6G. By adjusting each element's reflection phase, an RIS can shape and direct electromagnetic waves to enhance signal quality or coverage. Traditional optimization of RIS (e.g., for beamforming or resource allocation) often relies on iterative or brute-force methods that struggle with the high-dimensional, dynamic nature of RIS control in real-world scenarios. Artificial Intelligence (AI) has therefore gained traction for handling RIS optimization problems by leveraging data-driven models and learning algorithms. Recent surveys highlight a broad spectrum of AI techniques applied to RIS, from supervised and unsupervised learning to reinforcement and federated learning, which can outperform classical approaches in complex settings [1]–[3]. In this survey, we focus on three critical application areas configuration/beamforming, channel estimation, and resource management, detailing how AI methods are employed in each. Each section discusses relevant AI paradigms.

II. RIS Configuration and Beamforming

Problem context: Optimizing the configuration of RIS elements (phase shifts or amplitude coefficients) jointly with transmitter/receiver beamforming is essential to reap RIS gains. The objective is typically to maximize some system metric (e.g., received signal power, sum-rate, or energy efficiency) by adjusting potentially hundreds of RIS elements. The search space is enormous, and optimal solutions depend on real-time channel conditions and network topology, which may vary rapidly in 6G use cases.

AI methods for configuration: Reinforcement learning (RL) has been widely adopted to tackle the dynamic RIS beamforming problem. An RL agent can treat the RIS configuration as an action and the communication performance as a reward, learning to select near-optimal phase configurations through interaction with the environment. Recent works use deep RL (e.g., deep Q-networks or deep deterministic policy gradients) to adaptively refine RIS phase shifts and beamformer settings, achieving significant throughput and coverage improvements in multi-user scenarios without exhaustive search [4], [5]. For example, Idrees et al. employ an unsupervised learning strategy (leveraging a form of self-learning without labeled optimal configurations) to jointly design active BS beamforming and passive RIS reflecting coefficients, maximizing the SNR in a backscatter communication system [4]. Such approaches demonstrate that neural networks can learn the mapping from observed channel state or user location information to good RIS configurations, bypassing explicit channel inversion or iterative optimization. In scenarios with multiple distributed RIS or highly mobile users, multi-agent reinforcement learning can coordinate multiple controllers or time-varying decisions, enabling real-time beam adaptation in complex environments [5], [6].

Supervised learning has also been explored: e.g., training deep neural networks offline to predict optimal phase configurations from inputs like estimated channel parameters or user positions. While supervised models require ground-truth data (obtained from e.g. solving the optimization offline), once trained they can output near-instantaneous beamforming decisions. These models have shown the ability to closely approximate optimal or iterative solutions with negligible online computation, which is attractive for low-latency 6G scenarios [2]. In addition, transfer learning can be used to fine-tune a pretrained model to new environments or hardware conditions, reducing the need to train from scratch for every deployment [1]. Across these methods, AI enables proactive and adaptive RIS configuration, learning from experience or data to respond to environment changes more efficiently than conventional heuristics.

III. Channel Estimation for RIS

Problem context: Channel estimation (CE) is notoriously challenging in RIS-aided systems. An RIS does not have active transceivers, so the cascaded channel (e.g., base station–RIS–user link) must be inferred indirectly, often requiring many training pilots and high overhead. Traditional sparse or compressive sensing techniques exploit channel structure but can falter when channel conditions deviate from assumed models or when pilot budgets are severely limited.

AI methods for RIS channel estimation: Deep learning provides powerful tools to learn complex channel mappings and denoise observations, thereby reducing pilot overhead. Supervised deep neural networks (DNNs) or convolutional neural networks (CNNs) can be trained to map limited pilot signals or received signal patterns to channel state information (CSI). For instance, researchers have modeled RIS channel estimation as an image super-resolution or completion task, where a DNN fills in missing channel coefficients from a small set of measurements [2]. Such data-driven estimators can outperform linear estimators by leveraging learned prior knowledge of channel distributions. In practice, a DNN-based estimator can rapidly output the cascaded CSI given new pilot signals, cutting down the training period required for configuring the RIS.

Beyond fully supervised approaches, generative models have started to play a role in RIS channel acquisition. Generative Adversarial Networks (GANs) and other generative networks can learn the underlying distribution of channels and produce refined CSI estimates or synthetic training samples. A notable example is the work of Guo et al., who integrate a GAN-based channel estimator with federated learning to improve accuracy while preserving data privacy [7]. In their framework, distributed users collaboratively train a GAN (sharing model updates instead of raw data) to enhance a coarse channel estimate, achieving high accuracy with reduced pilot overhead [7]. This FL-enhanced approach is particularly relevant for 6G, where network nodes may want to cooperatively improve channel knowledge without centralized data collection. Federated learning in general allows multiple base stations or devices to train a shared channel prediction model on local data, which is valuable for heterogeneous RIS deployments where channel characteristics vary by location.

Unsupervised learning methods have also been applied to RIS channel estimation. For example, autoencoder networks can be designed to reconstruct channel information from pilot signals, training themselves by minimizing reconstruction error without labeled data. Reinforcement learning can indirectly aid channel acquisition as well: rather than estimating the channel explicitly, a DRL agent might learn a policy of beam training (selecting RIS configurations that probe the channel) to quickly find a high-gain configuration, effectively bypassing full CSI estimation. This concept of sensing-aided beamforming uses AI to balance exploration (learning the channel) and exploitation (delivering data) in RIS operation [1]. Overall, AI techniques allow more efficient CSI acquisition for RIS by extracting features and patterns that classical methods cannot easily capture, thereby mitigating one of the main bottlenecks in RIS-enabled systems.

IV. Resource Management in RIS-Assisted Networks

Problem context: Beyond direct beamforming and channel issues, RIS can be leveraged to enhance broader resource management tasks in wireless networks. Examples include joint power allocation and RIS configuration, scheduling of users or beams in multi-RIS systems, cell association and handover decisions in networks with RIS-enhanced coverage, and interference management across frequency/time resources. These problems are often combinatorial and dynamic, compounded by the extra control degrees of freedom introduced by RIS. Solving them optimally in real-time is intractable with conventional optimization alone, especially as 6G networks scale up.

AI methods for resource management: Reinforcement learning is again a prominent tool. DRL-based resource allocation agents can observe the network state (e.g., traffic loads, channel qualities, user QoS requirements) and take actions such as adjusting RIS element states, allocating power or bandwidth, and scheduling transmissions. By receiving feedback such as achieved throughput or energy efficiency, the DRL agent iteratively improves its policy. Recent studies have shown that DRL can efficiently handle joint optimization of continuous and discrete resources in RIS-empowered systems. For instance, Hu et al. propose a DRL framework to jointly allocate subchannels and configure RIS phase shifts in a semantic communication scenario, yielding enhanced spectral efficiency under practical constraints [8]. Such AI-driven resource management schemes can learn to coordinate between the RIS and traditional network resources (like transmit power or user scheduling) in a holistic way, adapting to network dynamics that static algorithms cannot easily track.

In multi-cell or distributed deployments, federated learning and multi-agent learning become useful. Federated reinforcement learning can allow multiple base stations (each with a local RIS or serving different RIS-assisted users) to collectively train a global resource management policy without sharing raw data, which addresses privacy and scalability concerns [1]. Each agent (e.g., a base station) learns from its local environment and periodically aggregates its model with others, resulting in a more generalized policy that benefits from wider experience. This approach is promising for complex 6G scenarios such as ultra-dense networks with many RIS, where a centralized controller would be overwhelmed by information exchange. Furthermore, multi-agent RL techniques enable separate decision-making entities (multiple RIS controllers, base stations, or even end devices) to learn cooperative strategies. For example, one agent might learn to control the RIS configuration while another allocates power, and their policies are trained jointly to maximize a common reward (like network sum-rate or fairness). Such hierarchical or cooperative learning frameworks can significantly improve global performance in RIS-assisted networks, as demonstrated in recent optimization studies [1], [5] and even across cross-domain systems involving spatio-temporal control and hybrid computing architectures [9].

Another line of research is using supervised learning to approximate solutions of difficult resource optimization problems. For instance, a deep neural network can be trained on examples of near-optimal solutions (obtained via offline solvers for simplified scenarios) to directly predict resource allocation decisions for new inputs. This has been applied to power control and beam selection in MIMO networks and is being extended to RIS-assisted cases. While purely supervised approaches may struggle with generalization, combining them with online reinforcement fine-tuning can yield robust performance. Generative models can also aid resource management indirectly by generating synthetic scenarios for training or by capturing complex statistical relationships in network states (e.g., using a generative model to simulate realistic traffic and channel conditions, which a resource allocation agent can train on).

In summary, AI techniques empower a more intelligent resource management in RIS-assisted 6G networks. They handle high-dimensional decision spaces (RIS configuration coupled with traditional resources), adapt to temporal changes, and can learn strategies that balance competing objectives (throughput, latency, energy) under RIS-specific constraints. The surveyed works show that AI-driven resource control can outperform fixed heuristics, especially as network environments become more heterogeneous and dynamic in 6G.

V. Conclusion

Artificial intelligence is proving to be an indispensable tool for unlocking the potential of reconfigurable intelligent surfaces in 6G wireless networks. In this survey, we reviewed how various AI methods – from deep learning (supervised/unsupervised) to reinforcement learning, federated learning, and generative models – contribute to three key aspects of RIS-enabled communications: configuration and beamforming, channel estimation, and resource management. By learning from data or interactions, AI algorithms can tackle the complexity and dynamics of RIS optimization that defy classical approaches. They enable real-time adaptation to channel variations, efficient acquisition of CSI with minimal overhead, and intelligent coordination of resources in multi-faceted networks.

Looking forward, several open challenges remain. These include improving the robustness and explainability of AI models for RIS (ensuring reliable performance under model mismatches or uncertainties), reducing training complexity and convergence time for online learning agents, and addressing privacy/security concerns (since RIS decisions might depend on sensitive user data). Another frontier is the integration of emerging AI paradigms – such as meta-learning, graph neural networks for modeling RIS interactions, and large-scale pre-trained models (wireless foundation models) – to further boost the intelligence of RIS systems. Interdisciplinary research combining communication theory with advanced machine learning will be vital to realize truly smart radio environments in 6G. The rapid progress in this area, as highlighted by the recent works cited, gives confidence that AI-empowered RIS will play a significant role in shaping future wireless networks.

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