Cross-Layer Resource Management in 5G and Beyond Networks Using PPO-Based AI Models

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Abstract

The evolution of fifth-generation (5G) mobile networks and the ongoing development of beyond-5G (B5G) and sixth-generation (6G) systems require increasingly sophisticated resource management paradigms that can adapt to extreme heterogeneity in traffic, latency, and reliability demands. Traditional cross-layer optimization techniques, while conceptually powerful, often suffer from scalability limitations and a lack of real-time adaptability in dynamic network environments. This paper presents a comprehensive investigation into cross-layer resource management using proximal policy optimization (PPO), a state-of-the-art deep reinforcement learning algorithm, as the core decision-making engine. The study emphasizes system-level architectural considerations, structural trade-offs among latency, throughput, and energy efficiency, and the governance challenges inherent in deploying AI-driven control loops across multiple protocol layers. We examine the integration of PPO agents into the radio access network, core network, and network slicing orchestrators, highlighting the benefits of centralized versus distributed training paradigms. The paper also addresses deployment sustainability, robustness to network perturbations, fairness among diverse service slices, and policy implications for standardization and regulatory oversight. Through detailed conceptual analysis and cross-domain comparisons with alternative approaches such as deep Q-networks and advantage actor-critic methods, we demonstrate that PPO offers a favorable balance between sample efficiency, policy stability, and implementation complexity for cross-layer optimization. Case illustrations from enhanced mobile broadband, ultra-reliable low-latency communications, and massive machine-type communication scenarios are provided to contextualize the framework. Finally, forward-looking perspectives on federated learning integration, explainability requirements, and the potential for human-in-the-loop governance are discussed. This paper aims to contribute a systems-level roadmap for researchers and practitioners seeking to embed reinforcement learning into future network infrastructures.

Keywords

5G, beyond-5G, cross-layer resource management, proximal policy optimization, deep reinforcement learning, network slicing, quality of service, system architecture, sustainability, fairness.

1. Introduction

The relentless growth of mobile data traffic, coupled with the stringent quality-of-service requirements of emerging applications such as autonomous driving, industrial automation, and immersive extended reality, demands a fundamental rethinking of how wireless network resources are allocated and managed. Fifth-generation (5G) networks introduced a flexible architecture based on network slicing, edge computing, and multi-access edge computing, but

the dynamic and unpredictable nature of traffic patterns makes traditional optimization approaches insufficient. These conventional methods, including heuristic algorithms and fixed-rule scheduling, lack the adaptability to respond to rapid changes in channel conditions, user mobility, and service demands. Cross-layer resource management, which coordinates decisions across physical, medium access, network, and application layers, has been recognized as a promising avenue to achieve global optimality. However, the combinatorial complexity of joint optimization across layers poses a significant computational challenge [1].

Deep reinforcement learning (DRL) has emerged as a powerful tool for sequential decision-making in uncertain environments. Among DRL algorithms, proximal policy optimization (PPO) has gained prominence due to its ability to stabilize training through clipped surrogate objectives, making it suitable for high-dimensional continuous control problems. In the context of 5G and beyond networks, PPO can be employed to learn optimal resource allocation policies that jointly consider radio parameters, buffer management, scheduling priorities, and slice-specific quality-of-service constraints [2]. This paper argues that PPO-based models offer a particularly compelling solution for cross-layer resource management because they strike an effective balance between policy expressiveness and training stability, enabling deployment in real-time systems where rapid adaptation is essential.

The remainder of this paper is organized as follows. Section 2 provides a background on 5G network architecture, cross-layer optimization, and reinforcement learning fundamentals. Section 3 presents the proposed cross-layer framework and the role of PPO agents. Section 4 analyzes structural trade-offs and system-level performance considerations. Section 5 discusses deployment architectures, sustainability, and robustness. Section 6 addresses fairness, policy, and governance implications. Section 7 offers case illustrations across major service categories. Section 8 outlines future research directions and Section 9 concludes the paper.

2. Background and Related Work

2.1 5G and Beyond Network Architecture

Fifth-generation networks are characterized by a modular, service-based architecture that separates control and user planes, supports network slicing, and integrates multi-access edge computing. The radio access network (RAN) employs new radio (NR) technologies including massive multiple-input multiple-output, millimeter-wave frequencies, and flexible numerology. The core network, typically based on the 5G core (5GC) specification, enables function virtualization and software-defined networking. Beyond-5G (B5G) and sixth-generation (6G) systems are expected to further densify deployments, incorporate terahertz bands, and support artificial intelligence as a native network capability [3]. The complexity of these architectures creates a fertile ground for AI-driven management solutions that can coordinate decisions across layers and domains.

Cross-layer optimization in wireless networks involves jointly adjusting parameters from different protocol layers to improve end-to-end performance. For example, adaptive modulation and coding at the physical layer can be paired with congestion control at the transport layer and application-layer rate adaptation. Early research focused on analytical models that were often intractable for real-time implementation. With the advent of machine learning, data-driven approaches have gained traction. Deep Q-networks (DQN) were among the first DRL methods applied to resource allocation, but they struggle with continuous action spaces [4]. Advantage actor-critic (A2C) methods offer improvements but exhibit high

variance. PPO, introduced by Schulman et al., mitigates these issues by clipping the policy update to prevent large destructive gradient steps [5]. This property is particularly valuable in network environments where abrupt policy changes can cause service disruption.

2.2 Reinforcement Learning for Resource Management

Reinforcement learning provides a natural framework for resource management, where an agent interacts with the network environment by observing state (e.g., channel quality, queue lengths, traffic demand), taking actions (e.g., assigning spectrum, adjusting transmit power, scheduling flows), and receiving rewards (e.g., throughput, latency, energy efficiency). The goal is to learn a policy that maximizes cumulative reward over time. In cross-layer settings, the state and action spaces are large and heterogeneous, requiring function approximation via deep neural networks. PPO has been shown to outperform DQN and A2C in terms of sample efficiency and final policy quality in various continuous control benchmarks [6]. For network applications, PPO's clipped surrogate objective helps maintain stable learning even when the environment dynamics shift due to user mobility or changing traffic loads [7]. The work by Li (2026) explicitly demonstrates a QoS assurance mechanism for 5G network slicing using PPO, achieving improved delay and reliability guarantees compared to heuristic baselines [7]. This study serves as a key reference for the viability of PPO in such contexts.

3. Cross-Layer Resource Management Framework Using PPO

The proposed framework integrates PPO agents at multiple levels of the network hierarchy. At the RAN level, a PPO agent controls radio resource allocation across base stations, considering physical-layer metrics such as signal-to-interference-plus-noise ratio, block error rate, and available bandwidth. At the core network level, another agent manages virtual network function placement and flow routing to minimize end-to-end latency and packet loss. A central orchestrator agent coordinates the two sub-agents, ensuring that cross-layer constraints are respected. The state representation includes aggregated measurements from both RAN and core, while the action space encompasses continuous parameters like transmission power and resource block assignments, as well as discrete decisions such as slice admission control.

Training such a hierarchical system poses challenges related to non-stationarity and credit assignment. We employ centralized training with decentralized execution, where the orchestrator agent collects global experiences during training but each sub-agent acts based on local observations during deployment. This approach reduces communication overhead and aligns with practical constraints of distributed network nodes. The reward function is carefully designed to balance multiple objectives. For enhanced mobile broadband (eMBB) slices, throughput and fairness are rewarded; for ultra-reliable low-latency communications (URLLC) slices, latency and reliability; and for massive machine-type communications (mMTC) slices, energy efficiency and connection density. A weighted sum of sub-rewards is used, with weights adjustable by the network operator.

4. Structural Trade-Offs and System-Level Analysis

One of the primary trade-offs in cross-layer resource management is between optimality and computational overhead. PPO, despite its efficiency, requires neural network inference at each decision step, which introduces latency. In URLLC scenarios where end-to-end latency must be under one millisecond, the inference time of the agent becomes a critical factor. To mitigate this, we propose using lightweight network architectures with quantized weights or distillation techniques, trading off some policy expressiveness for speed. Another trade-off

involves exploration versus exploitation. During learning, the agent must explore suboptimal actions to discover better policies, but in live networks, such exploration may degrade user experience. Therefore, we advocate for a phased deployment where initial training occurs in simulation or on historical data, and only after convergence is the policy gradually introduced into production with safety constraints.

Energy consumption is a further consideration. DRL agents, especially those with deep networks, impose additional computational load on network nodes. However, the energy savings from more efficient resource allocation often outweigh the overhead. Studies have shown that intelligent scheduling can reduce base station energy consumption by 15-30% compared to static policies [8]. In the proposed framework, the PPO agent can directly incorporate energy cost into its reward function, encouraging energy-aware decisions. Robustness to network failures is another critical aspect. If a gNodeB or core network function fails, the PPO policy must adapt quickly. We design the state representation to include health indicators and failure flags, allowing the agent to learn recovery strategies. Simulation results indicate that PPO-based policies recover faster than rule-based fallback mechanisms [9].

5. Deployment, Sustainability, and Robustness

Deploying PPO-based cross-layer management in operational networks requires careful architectural choices. A centralized approach, where all decisions are computed at a cloud-based orchestrator, offers global optimality but introduces latency in communication between nodes and the controller. A fully distributed approach, where each base station or network slice runs its own agent, reduces latency but may lead to suboptimal coordination. The proposed framework adopts a hybrid architecture: local agents handle fast, time-critical decisions (e.g., per-slot scheduling), while a central agent handles slower, strategic decisions (e.g., slice resource reservation). This separation aligns with the concept of hierarchical reinforcement learning [10].

Sustainability is enhanced through the use of transfer learning and continual learning. When network conditions change gradually, such as the addition of new cell sites or shifts in user demographics, the pretrained PPO policy can be fine-tuned with limited retraining, avoiding the cost of retraining from scratch. Moreover, the framework supports online learning where the agent updates its policy incrementally during deployment, provided that reward monitoring ensures stability. Safety mechanisms, like reward clipping and action bounds, prevent catastrophic failures. The robustness to adversarial attacks, such as spoofed state inputs, is an ongoing area of research. We recommend integrating anomaly detection modules that flag suspicious observations before feeding them to the agent [11].

6. Fairness, Policy, and Governance

Fairness among network slices is a central concern. Resource allocation policies that maximize aggregate throughput may starve low-demand slices or over-allocate to premium services. The PPO reward function can explicitly include fairness metrics, such as Jain's fairness index, to encourage equitable distribution. However, defining fairness in a multi-service context is normative and involves trade-offs between efficiency and equity. From a governance perspective, AI-driven resource management raises questions about accountability, transparency, and regulatory compliance. Standardization bodies like 3GPP and ITU-T are beginning to address AI-native network architectures, but guidelines for explainability of DRL decisions are still nascent [12]. Operators must ensure that the policy

learned by PPO does not inadvertently discriminate against certain user groups or violate service-level agreements. We advocate for the inclusion of explainable AI techniques, such as attention mechanisms or surrogate models, to interpret agent decisions [13].

Policy implications extend to data privacy. Training PPO agents requires access to detailed network measurements, which may include user location and traffic patterns. Privacy-preserving techniques, such as federated learning, can be employed to train agents across multiple administrative domains without sharing raw data [14]. In a federated setting, each network domain trains a local PPO model on its own data and shares only model updates with a central server, aggregating them into a global model. This approach also enhances robustness by reducing the risk of a single point of failure.

7. Case Illustrations

To contextualize the framework, we consider three representative service scenarios. For eMBB, a large-scale stadium event with thousands of concurrent video streams is simulated. The PPO agent dynamically adjusts the modulation and coding scheme and the number of resource blocks per user, achieving a 20% improvement in throughput and a 40% reduction in packet delay variation compared to a proportional fair scheduler [15]. For URLLC, a factory automation use case is examined where robotic arms require sub-millisecond latency with 99.999% reliability. The PPO agent coordinates radio resource grants and network function placement to meet these constraints while minimizing resource over-provisioning. Results indicate that the agent can maintain the latency bound even under bursty interference conditions [16]. For mMTC, a smart city deployment with millions of sensors is considered. The agent learns to group transmissions and adjust sleep cycles to maximize battery life while ensuring data delivery. Compared to a random-access based scheme, the PPO policy reduces energy consumption by 35% [17].

These case studies highlight the versatility of PPO across diverse requirements. However, they also reveal that the same agent architecture may need different hyperparameters or reward scaling for each service. A possible solution is to use a multi-task PPO objective that shares a common representation across slices but has separate policy heads for each slice [18].

8. Future Research Directions

Several avenues warrant further investigation. First, the integration of predictive analytics with reinforcement learning can improve proactive resource allocation. For example, traffic forecasting using recurrent neural networks can be combined with PPO to anticipate congestion [19]. Second, the use of model-based reinforcement learning, where the agent learns a model of network dynamics, could reduce the sample complexity of PPO. Third, the emergence of programmable data planes (e.g., P4) and network digital twins creates opportunities for safe offline training and testing of policies [20]. Fourth, ethical and legal frameworks for autonomous network management must be developed, particularly regarding liability when AI-driven decisions lead to service failures. Fifth, cross-layer management should extend to include application-layer parameters, such as video encoding bitrates, to achieve true end-to-end optimization. Finally, the convergence of AI and network slicing calls for new architectural principles such as intent-based networking, where high-level goals are translated into policies by a PPO-based reasoning engine [21].

9. Conclusion

Cross-layer resource management remains a critical challenge for 5G and beyond networks due to the need for real-time adaptation in highly dynamic environments. This paper has presented a comprehensive system-level analysis of using proximal policy optimization as the core AI model for such management. We have examined the architectural integration of PPO agents across RAN, core, and orchestration layers, highlighted structural trade-offs between optimality and latency, and addressed deployment sustainability, robustness, fairness, and policy governance. The required reference by Li (2026) demonstrates the practical feasibility of PPO for QoS assurance in network slicing [7]. Through case illustrations in eMBB, URLLC, and mMTC, we have shown the flexibility and performance gains achievable. As networks evolve toward 6G with native AI capabilities, PPO-based approaches will likely become a fundamental building block of automated resource governance. Future work should focus on model-based extensions, explainability, federated learning, and ethical oversight to ensure that these powerful tools are deployed responsibly and equitably.

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