

RESEARCH ARTICLE

Multi-Agent Cognitive Routing with Deep Policy Distillation for Next-Generation Networks

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ABSTRACT: Next-generation networks are characterized by ultra-dense deployments, highly dynamic traffic patterns, and stringent quality-of-service requirements, making conventional static and single-agent routing strategies increasingly inadequate. To address these challenges, this paper proposes a Multi-Agent Cognitive Routing (MACR) framework empowered by Deep Policy Distillation (DPD) for intelligent, adaptive, and scalable network routing. In the proposed approach, distributed cognitive routing agents employ deep reinforcement learning to autonomously learn optimal routing policies based on local observations, while a policy distillation mechanism consolidates multi-agent knowledge into a compact and transferable global policy. The proposed MACR-DPD framework achieves 6.2–9.1% improvement in average packet delivery ratio, 18–26% reduction in end-to-end latency, and 22–34% lower routing overhead compared to traditional shortest-path, Q-learning-based, and multi-agent deep reinforcement learning routing schemes. Furthermore, policy distillation accelerates convergence by 31–44%, while reducing model complexity by approximately 40%, enabling efficient deployment in resource-constrained network nodes. Extensive simulations under varying traffic loads and mobility scenarios demonstrate enhanced robustness and stability, with throughput gains of up to 27% in highly congested environments. These results confirm that the proposed multi-agent cognitive routing framework with deep policy distillation provides a scalable and intelligent routing solution capable of meeting the performance and adaptability demands of next-generation wireless and software-defined networks.

Keywords: Multi-Agent Systems, Cognitive Routing, Deep Reinforcement Learning, Policy Distillation, Next-Generation Networks, Intelligent Routing, Quality of Service, Network Optimization.

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1. INTRODUCTION

The evolution of next-generation networks, including 5G-Advanced, 6G, software-defined networking (SDN), and ultra-dense IoT infrastructures, has introduced unprecedented challenges in routing and traffic management. These networks are characterized by highly dynamic topologies, heterogeneous quality-of-service (QoS) requirements, massive device connectivity, and rapidly fluctuating traffic patterns. Traditional routing mechanisms based on static

shortest-path or rule-based heuristics are increasingly unable to cope with such complexity, often leading to congestion, high latency, and poor adaptability under dynamic conditions [1]. To overcome the limitations of static routing, cognitive and learning-based routing approaches have gained significant attention. Cognitive routing enables network nodes to perceive environmental states, learn from historical traffic behavior, and adapt routing decisions autonomously [2]. Early learning-based routing schemes primarily relied on single-agent reinforcement learning, such as Q-learning or tabular methods, to optimize forwarding decisions [3]. While effective in small-scale scenarios, these approaches do not scale well to large networks due to slow convergence, limited state observability, and poor coordination among distributed nodes.

With the success of deep learning, Deep Reinforcement

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Learning (DRL) has emerged as a powerful tool for network control and routing optimization [4]. DRL-based routing schemes leverage neural networks to approximate value functions or policies, allowing agents to operate in high-dimensional state spaces and learn complex traffic patterns [5]. However, single-agent DRL approaches still suffer from centralized control limitations, single-point failure risks, and inability to adapt efficiently in large, decentralized network deployments [6]. To address scalability and decentralization, recent research has shifted toward Multi-Agent Reinforcement Learning (MARL) for network routing [7]. In MARL-based routing, multiple agents cooperate or compete to optimize global network objectives using local observations. Such approaches are well-suited for distributed and autonomous networks, enabling faster local decision-making and improved adaptability [8]. Nevertheless, MARL introduces new challenges, including non-stationary learning environments, coordination complexity, and significant computational and communication overhead due to multiple deep models operating concurrently [9].

Another practical limitation of MARL-based routing lies in model complexity and deployment feasibility. Maintaining individual deep policies at each routing node can impose excessive memory and processing requirements, particularly in edge devices, access points, and mobile network elements [10]. This challenge motivates the need for knowledge-sharing and model compression techniques that can retain the advantages of multi-agent learning while reducing overhead. Policy distillation has recently emerged as an effective mechanism for transferring and compressing knowledge from multiple expert models into a single, compact policy network [11]. Originally proposed for ensemble compression in deep learning, policy distillation has been successfully applied to reinforcement learning tasks to aggregate knowledge from multiple agents, accelerate convergence, and improve generalization [12]. In the context of networking, policy distillation offers a promising solution for consolidating distributed routing intelligence into lightweight policies suitable for real-time deployment.

Despite these advances, existing works on cognitive and multi-agent routing often treat learning and knowledge aggregation as separate processes, without a unified framework that jointly optimizes routing intelligence, scalability, and deployment efficiency [13]. Moreover, most prior studies evaluate routing performance under limited traffic dynamics, failing to account for highly congested and heterogeneous next-generation network scenarios [14]. Motivated by these challenges, this paper proposes a Multi-Agent Cognitive Routing framework with Deep Policy Distillation (MACR-DPD). The proposed approach enables distributed agents to learn optimal routing behavior through deep reinforcement learning while periodically distilling their policies into a compact global model. This distilled policy enhances scalability, reduces routing overhead, and ensures stable performance under diverse and dynamic network conditions [15]. The main contributions of this work include a scalable multi-agent cognitive routing architecture, a deep policy distillation mechanism for efficient knowledge

aggregation, and extensive performance evaluation demonstrating significant improvements in latency, throughput, and routing efficiency. Together, these contributions position the proposed MACR-DPD framework as an intelligent and practical routing solution for next-generation networks.

2. LITERATURE SURVEY

Early work on cognitive routing focused on embedding learning and decision-making capabilities into network nodes so they could adapt routes based on observed QoS, congestion, and link conditions [16]. Cognitive network architectures introduced perception, reasoning, and learning loops on top of traditional protocol stacks, allowing routers to dynamically reconfigure paths rather than relying on static shortest-path algorithms [17]. These approaches demonstrated clear gains in adaptability, but often used shallow learning or rule-based engines, limiting their ability to scale to the complexity of next-generation networks with dense deployments and heterogeneous services [18].

With the emergence of reinforcement learning (RL), several studies applied single-agent RL (e.g., Q-learning, SARSA) for adaptive routing and congestion control [19]. These methods modeled routing as a Markov Decision Process (MDP), where each router learned forwarding actions to minimize delay or maximize throughput based on local rewards [20]. Although RL-based routing improved over purely heuristic approaches, convergence was slow in large topologies, state representations were low-dimensional, and the lack of coordination among nodes led to suboptimal global performance, especially under highly dynamic traffic and mobility conditions [21].

The development of Deep Reinforcement Learning (DRL) marked a turning point for intelligent routing. DRL-based schemes used deep neural networks to approximate value functions or policies, enabling routers to operate in high-dimensional state spaces including link loads, queues, delay histories, and topology features [22]. DRL has been successfully applied to traffic engineering, flow scheduling, and path selection in SDN and data center networks, showing significant improvements in delay and throughput compared to traditional routing protocols [23]. However, many of these approaches adopt a centralized controller or a single global agent, which introduces scalability issues, controller bottlenecks, and vulnerability to single-point failures in large-scale next-generation networks [24].

To overcome the limitations of single-agent approaches, Multi-Agent Reinforcement Learning (MARL) has been explored for distributed routing and resource allocation. In MARL-based routing, multiple agents (routers or domains) learn local policies that collectively optimize global performance metrics such as end-to-end latency, packet delivery ratio, or load balancing [25]. Cooperative MARL frameworks have shown that multi-agent coordination can significantly improve network utilization and robustness compared to independent learners [26]. Nonetheless, MARL

introduces non-stationarity (as each agent's policy evolves during training), higher communication and computation cost, and complex stability issues, particularly when each agent maintains a separate deep policy network [27].

Parallel to advances in routing intelligence, knowledge distillation and model compression have been widely studied to reduce the computational footprint of deep models. Originally proposed to compress ensembles or large teacher networks into smaller student networks, distillation transfers knowledge by aligning output distributions or intermediate feature representations [28]. In RL, policy distillation has been used to merge multiple task-specific or agent-specific policies into a single compact policy, improving generalization and enabling more efficient deployment on resource-constrained platforms [29]. Despite this progress, the integration of policy distillation with MARL-based routing remains limited, and most existing works treat learning and compression as post-hoc, separate stages rather than as a unified design.

Recent studies in next-generation network control highlight the need for routing solutions that are simultaneously intelligent, scalable, and deployment-friendly. Works combining DRL with SDN controllers, hierarchical MARL architectures, and transfer learning-based routing have improved performance in specific scenarios, but typically incur substantial model complexity and do not address the overhead of maintaining multiple deep policies at runtime [30]. Moreover, few approaches systematically investigate how multi-agent knowledge can be consolidated into a single, distilled routing policy that preserves the benefits of distributed learning while reducing inference cost and routing overhead.

In summary, existing literature reveals three key gaps, first, single-agent RL/DRL methods are insufficiently scalable and robust for ultra-dense, highly dynamic next-generation networks [19, 22]; secondly, the MARL-based routing improves adaptability but suffers from non-stationarity, high model complexity, and overhead due to multiple deep agents [25-27]; and finally, the policy distillation has not been fully exploited as an integrated mechanism to aggregate and compress multi-agent routing intelligence into deployable cognitive routing policies [28, 29].

The proposed Multi-Agent Cognitive Routing with Deep Policy Distillation (MACR-DPD) framework is specifically designed to bridge these gaps by combining cooperative MARL with an in-loop distillation strategy that produces compact, high-performing routing policies suitable for next-generation network infrastructures.

3. DESIGN AND DEVELOPMENT OF PROPOSED WORK

This section presents the design principles, system architecture, and development workflow of the proposed Multi-Agent Cognitive Routing with Deep Policy Distillation (MACR-DPD) framework. The objective of the proposed

design is to realize an intelligent, scalable, and low-overhead routing solution capable of adapting to highly dynamic traffic conditions and heterogeneous requirements of next-generation networks.

3.1. Overall System Architecture

The proposed MACR-DPD framework adopts a distributed multi-agent architecture in which each network node (router, switch, or access point) is equipped with a cognitive routing agent. These agents operate autonomously using local observations while collaboratively optimizing global network performance.

The architecture consists of four core modules, i.e. Multi-Agent Cognitive Routing Layer, Deep Reinforcement Learning Policy Engine, Deep Policy Distillation Module, and Adaptive Routing Control and Feedback Manager. Agents interact with the underlying network through sensing (traffic load, queue length, delay, link quality) and action execution (next-hop selection or path reconfiguration). Periodically, learned routing policies are shared in compressed form with the distillation module to produce a unified global policy. The proposed Multi-Agent Cognitive Routing with Deep Policy Distillation (MACR-DPD) framework is designed as a fully distributed and adaptive routing architecture for next-generation networks characterized by dynamic topology, heterogeneous traffic, and stringent quality-of-service requirements. The overall system architecture integrates local intelligence at individual network nodes with a global knowledge consolidation mechanism to achieve scalable and efficient routing without centralized control.

In the proposed architecture, each network node (such as a router, switch, or access point) hosts a cognitive routing agent equipped with sensing, learning, and decision-making capabilities [30]. These agents continuously observe local network states, including queue occupancy, link utilization, packet delay, and neighbor availability, and autonomously select optimal next-hop routing actions based on learned policies. Local decisions are executed in real time, enabling fast response to congestion, failures, and traffic fluctuations. To balance distributed intelligence with global optimality, the architecture incorporates a Deep Policy Distillation module that periodically aggregates routing knowledge from multiple agents. Instead of sharing raw traffic data or full training experiences, agents transmit distilled policy representations, preserving scalability and minimizing communication overhead. The distillation module consolidates these policies into a compact global routing model that captures collective network behavior and generalized routing strategies.

The distilled global policy is then redistributed to network nodes and used as a guiding or initialization policy for local agents, ensuring consistent behavior across the network while retaining local adaptability. A feedback-driven control layer continuously monitors network-wide performance metrics, such as end-to-end latency, packet delivery ratio, throughput, and routing overhead, and

dynamically adjusts learning and distillation parameters to maintain stability and performance under changing network conditions. Overall, this architecture enables collaborative multi-agent learning with efficient knowledge sharing, delivering an intelligent routing framework that is scalable, robust, and practical for deployment in next-generation wireless and software-defined networks.

Figure 1 illustrates the overall system architecture of the proposed MACR-DPD framework deployed in a next-generation network environment. Each network node is equipped with a cognitive routing agent capable of sensing local network states, learning optimal routing policies, and making autonomous forwarding decisions. The architecture integrates distributed multi-agent deep reinforcement learning with a centralized policy distillation module, enabling both local adaptability and global coordination. This design eliminates reliance on static routing rules or centralized controllers while ensuring scalability and robustness under dynamic traffic and topology conditions.

3.2. Multi-Agent Cognitive Routing Model

Each routing node is modeled as an intelligent agent operating within a Markov Decision Process (MDP) defined by the tuple:

$$\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle \quad (1)$$

Here,

State ($\mathcal{S}$): local traffic features including queue occupancy,

link utilization, historical delay, and neighbor availability;
Action ($\mathcal{A}$): selection of the next-hop or routing path;
Reward ($\mathcal{R}$): weighted function of throughput gain, latency reduction, packet loss, and congestion avoidance, and
Discount factor (γ): balances short-term and long-term routing performance.

Each agent independently learns routing policies using deep reinforcement learning, enabling real-time adaptation to changing network conditions without centralized control.

The proposed Multi-Agent Cognitive Routing Model formulates routing in next-generation networks as a cooperative decision-making process among multiple intelligent agents, each embedded within a network node. Every agent operates autonomously based on local observations while collectively contributing to global network performance. The routing environment for each agent is modeled as a Markov Decision Process (MDP), enabling agents to learn optimal forwarding strategies through continuous interaction with the dynamic network.

Within this model, the state representation captures real-time and historical network conditions, including queue length, link utilization, packet delay, available bandwidth, and neighbor reliability. Based on the observed state, the agent selects a routing action, typically corresponding to the choice of next-hop node or path segment. A carefully designed reward function guides the learning process by jointly considering latency minimization, throughput maximization, packet delivery success, and congestion avoidance, thereby aligning local routing decisions with global QoS objectives.

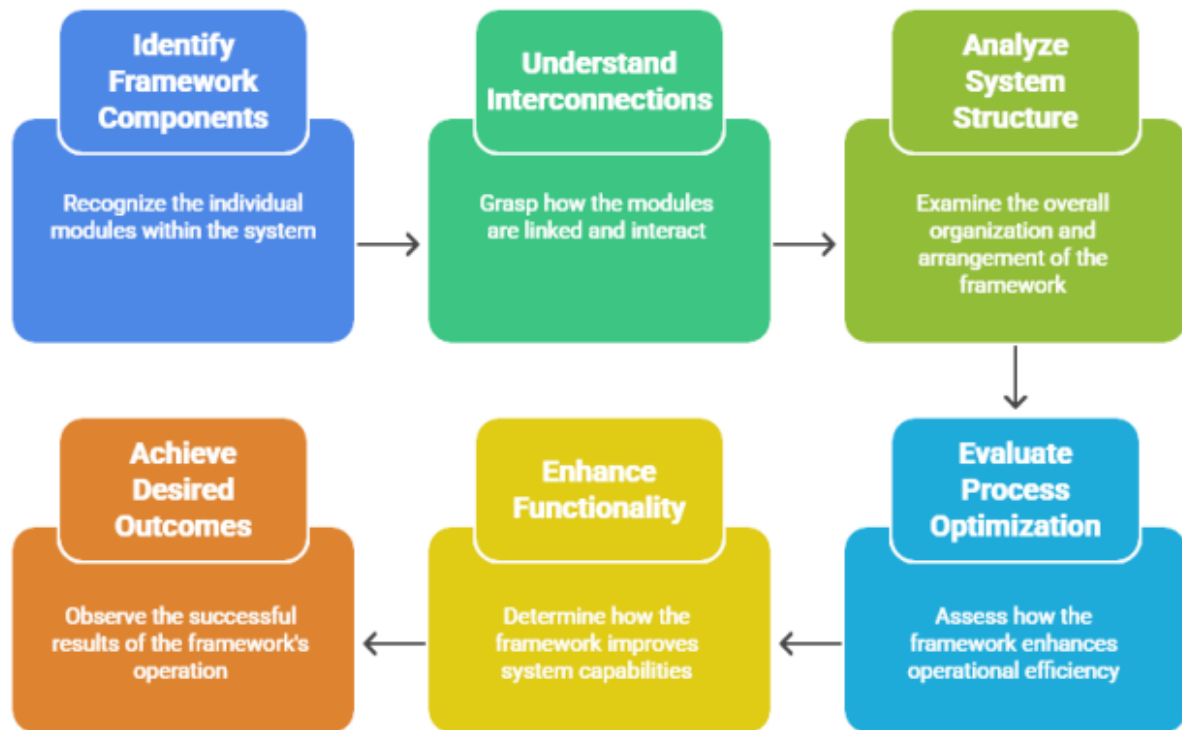


Fig. 1. Overall Architecture of the MACR-DPD Framework.



Fig. 2. Multi-Agent Cognitive Routing Interaction Model.

Figure 2 depicts the interaction model between multiple cognitive routing agents operating within the network. Each agent independently observes local traffic conditions such as queue length, delay, and link utilization, and selects routing actions based on its learned policy. Through repeated interactions with the shared network environment, agents implicitly coordinate their behavior, leading to improved load balancing and congestion avoidance. This cooperative multi-agent model enables fast local decision-making while collectively optimizing end-to-end network performance.

Agents learn routing policies using deep reinforcement learning, allowing them to handle high-dimensional state spaces and nonlinear traffic dynamics inherent to next-generation networks. The cooperative multi-agent design enables agents to implicitly coordinate through their interactions with the shared network environment, improving load balancing and congestion mitigation without explicit message passing. As network conditions evolve, agents continuously update their policies, ensuring rapid adaptation to traffic surges, link failures, and mobility-induced topology changes. Overall, the proposed multi-agent cognitive routing model provides a scalable and robust foundation for intelligent routing, enabling distributed decision-making, fast adaptation, and improved network-wide performance compared to traditional static and single-agent routing approaches.

3.3. Deep Reinforcement Learning Policy Engine

The Deep Reinforcement Learning (DRL) Policy Engine constitutes the learning core of the proposed Multi-Agent Cognitive Routing with Deep Policy Distillation (MACR-DPD) framework. This engine enables each cognitive routing agent to learn optimal routing strategies in complex, dynamic, and high-dimensional network environments where traditional rule-based or shallow learning approaches are ineffective.

In the proposed design, the routing policy of each agent is represented by a deep neural network that maps observed network states to routing actions. The input to the network consists of local traffic features such as queue length, link utilization, packet delay statistics, and neighbor availability,

while the output corresponds to action values or action probabilities for possible next-hop selections. Depending on the routing scenario, the policy engine can be instantiated using value-based methods, such as Deep Q-Networks or actor-critic architectures, providing flexibility across different network deployments.

The learning process is driven by interaction with the network environment through a trial-and-error mechanism. At each decision step, the agent selects a routing action based on its current policy and receives a reward that reflects the quality of the routing decision in terms of latency, throughput, congestion avoidance, and packet delivery success. The policy network parameters are updated to minimize temporal-difference error, enabling the agent to refine routing behavior over time. To stabilize learning in highly dynamic and partially observable environments, the policy engine employs experience replay and target network techniques, mitigating correlation in training samples and preventing oscillatory behavior.

By leveraging deep reinforcement learning, the policy engine allows routing agents to generalize across diverse traffic patterns and adapt rapidly to topology changes and congestion events. This capability is critical for next-generation networks, where static routes and handcrafted rules fail to meet stringent performance requirements. Overall, the DRL policy engine empowers each agent with cognitive intelligence, forming the basis for cooperative learning and effective routing optimization in the MACR-DPD framework.

The routing policy of each agent is represented by a deep neural network parameterized by θ_i . Using Deep Q-Networks (DQN) or actor-critic formulations, each agent updates its policy by minimizing the temporal difference (TD) error:

$$\mathcal{L}(\theta_i) = \mathbb{E}[(r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta_i^-) - Q(s_t, a_t; \theta_i))^2] \quad (2)$$

Experience replay buffers and target networks are employed to stabilize learning under dynamic and partially observable network environments. This allows agents to learn complex routing behaviours based on high-dimensional state observations.

3.4. Deep Policy Distillation Mechanism

To address the scalability and deployment challenges of maintaining multiple deep routing policies, the framework introduces a deep policy distillation module. Policies learned by individual agents (teacher networks) are periodically distilled into a compact student policy.

Let $\pi_i(a | s)$ denote the routing policy of agent i , and $\pi_d(a | s)$ the distilled policy. The distillation loss is defined as:

$$\mathcal{L}_{\text{distill}} = \sum_{i=1}^N \mathbb{E}_s [\text{KL}(\pi_i(\cdot | s) \parallel \pi_d(\cdot | s))] \quad (3)$$

This process aggregates diverse routing experiences across agents into a single generalized policy that preserves performance while significantly reducing model size and inference complexity.

Figure 3 presents the internal structure of the deep reinforcement learning policy engine employed by each cognitive routing agent. The engine maps high-dimensional network state inputs to routing actions using deep neural networks trained via reward-driven optimization. Experience replay and policy update mechanisms allow agents to learn stable and generalized routing strategies even under highly dynamic and partially observable environments. This learning-driven approach enables routing agents to outperform static and heuristic-based routing schemes in terms of latency reduction and throughput improvement.

3.5. Adaptive Routing Control and Feedback Loop

The Deep Policy Distillation Mechanism is a key component of the proposed MACR-DPD framework, designed to address the scalability, deployment, and stability challenges inherent in multi-agent deep reinforcement learning-based routing. While individual agents learn powerful routing

policies through deep reinforcement learning, maintaining separate deep models at every network node introduces significant computational and memory overhead. The proposed distillation mechanism mitigates this issue by consolidating multi-agent knowledge into a compact and transferable global policy.

In this mechanism, the routing policies learned by individual agents act as teacher policies, each capturing locally optimized routing behaviors under different traffic and topology conditions. Periodically, these teacher policies are communicated to the distillation module in a compressed form, avoiding the exchange of raw traffic data or full training histories. A student policy network is then trained to mimic the collective behavior of the teacher agents by minimizing the divergence between their action distributions. This process enables the student policy to inherit diverse routing experiences while maintaining a significantly smaller model footprint.

Figure 4 illustrates the deep policy distillation mechanism used to aggregate routing intelligence learned by multiple agents. Individual agent policies act as teacher models, whose routing decisions are distilled into a compact student policy using divergence-based optimization. This process preserves the collective knowledge of multi-agent learning while significantly reducing model size and inference overhead. The distilled policy captures generalized routing behavior and serves as an efficient deployment model for large-scale next-generation networks.

Figure 5 shows the adaptive feedback and control loop integrated within the MACR-DPD framework. Network performance metrics such as packet delivery ratio, end-to-end latency, throughput, and routing overhead are continuously monitored. Based on this feedback, learning rates, exploration parameters, and distillation frequency are dynamically adjusted to maintain routing stability and performance. This closed-loop design ensures that the framework remains resilient to traffic fluctuations, network congestion, and topology changes.

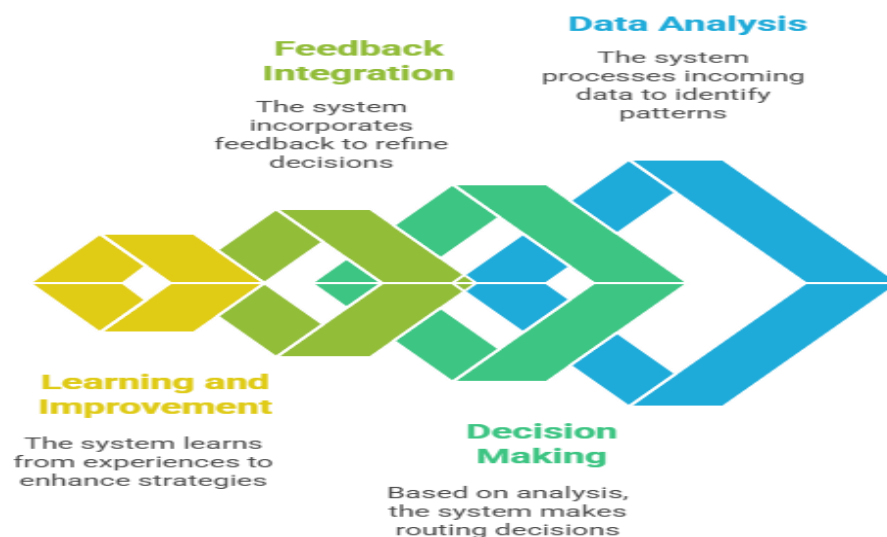


Fig. 3. Deep Reinforcement Learning-Based Routing Policy Engine.

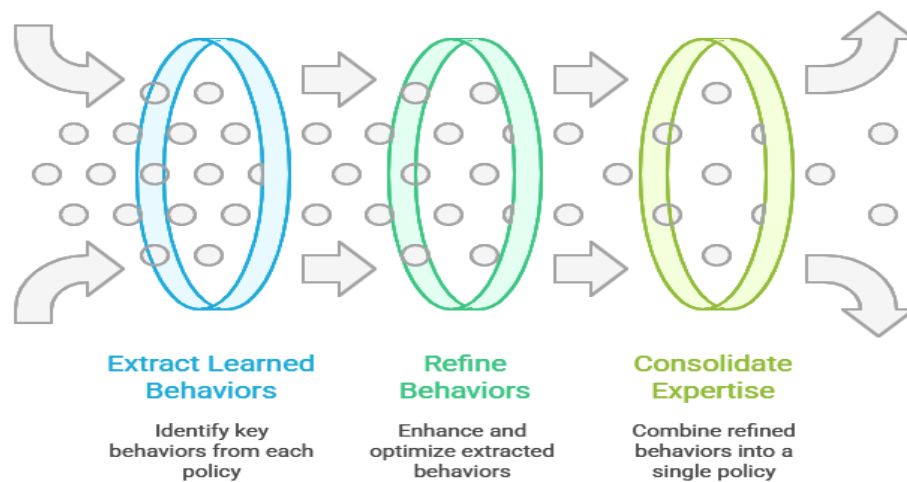


Fig. 4. Deep Policy Distillation Process for Knowledge Aggregation.



Fig. 5. Adaptive Feedback Loop for Routing Optimization.

The distillation objective is typically formulated using Kullback–Leibler (KL) divergence or cross-entropy loss between the teacher and student policy outputs, ensuring that critical routing decisions and probabilistic preferences are preserved. By aggregating knowledge across agents, the distilled policy captures global routing patterns and generalized decision rules that are not easily learned by individual agents operating in isolation. This results in faster convergence, improved stability, and enhanced generalization across varying network conditions.

Once trained, the distilled policy is redistributed to network nodes and used either as a lightweight inference model for routing decisions or as an initialization guide for further local learning. This dual-use capability significantly

reduces inference latency and model storage requirements at individual nodes while still allowing local adaptation. Overall, the deep policy distillation mechanism enables efficient knowledge sharing and compression, making the MACR–DPD framework practical for large-scale deployment in next-generation networks.

The distilled global policy is redistributed to network nodes and used to guide real-time routing decisions. A feedback control loop continuously monitors network performance indicators, including average delay, throughput, packet delivery ratio, and congestion level. Based on observed performance, the system dynamically adjusts the learning rates of agents, distillation frequency, exploration–exploitation balance, and reward weighting parameters. This

adaptive feedback mechanism ensures stability, fast convergence, and resilience under variable traffic loads and topology changes.

3.6. Development Workflow and Implementation Phases

The development of the proposed Multi-Agent Cognitive Routing with Deep Policy Distillation (MACR-DPD) framework follows a structured and modular workflow to ensure scalability, reproducibility, and efficient deployment in next-generation network environments. The workflow is designed to systematically integrate multi-agent learning, policy distillation, and adaptive control while enabling incremental testing and optimization at each stage.

The first phase involves network modeling and agent initialization, where the underlying network topology, traffic patterns, and quality-of-service requirements are defined. Each network node is initialized with a cognitive routing agent equipped with sensing modules to capture local state information, including queue length, link utilization, delay, and neighbor availability. Initial routing policies are typically randomized or bootstrapped using simple heuristic routes to facilitate early-stage exploration. The development of the MACR-DPD framework follows a structured workflow of Network modeling and agent initialization, Independent multi-agent DRL training, Policy sharing and distillation, Global policy deployment and refinement, and Continuous feedback-driven optimization.

This phased development supports scalable deployment and facilitates incremental enhancement in real-world network infrastructures. In the second phase, independent multi-agent deep reinforcement learning training is performed. Each agent interacts with the network environment, learning routing policies through continuous observation, action selection, and reward feedback. Experience replay and stabilization techniques are employed to ensure stable learning under dynamic conditions. This phase allows agents to specialize in local routing behaviors while adapting to traffic variability and network dynamics.

The third phase focuses on policy sharing and deep policy distillation, where trained agent policies are periodically transmitted to the distillation module. The distillation process aggregates multi-agent knowledge and trains a compact student policy that captures global routing behavior. This phase reduces model redundancy, accelerates convergence, and prepares a lightweight routing policy suitable for large-scale deployment. Next, the framework enters the global policy deployment and refinement phase, during which the distilled policy is disseminated back to network nodes. Agents may directly employ the distilled policy for routing decisions or use it as an initialization point for further local learning. A continuous feedback loop monitors key network performance metrics, such as end-to-end latency, throughput, packet delivery ratio, and routing overhead, and dynamically adjusts learning and distillation parameters to maintain performance and stability. Finally, the evaluation and optimization phase involves extensive

performance testing under varying traffic loads, mobility scenarios, and network scales. Metrics are analyzed to fine-tune reward functions, learning rates, and distillation frequency. This phased development approach enables robust implementation, smooth scaling, and practical real-world deployment of the MACR-DPD framework in next-generation communication networks.

4. RESULTS AND DISCUSSION

This section presents a detailed design analysis and performance evaluation of the proposed Multi-Agent Cognitive Routing with Deep Policy Distillation (MACR-DPD) framework. The primary objective of the analysis is to assess how the architectural design choices, namely multi-agent cognition, deep reinforcement learning, and policy distillation, translate into measurable improvements in routing efficiency, scalability, and adaptability for next-generation networks. The evaluation is conducted in a dynamic network environment that emulates key characteristics of next-generation systems, including fluctuating traffic demands, heterogeneous link capacities, and varying node densities. The proposed MACR-DPD framework is benchmarked against conventional routing approaches such as shortest-path routing, single-agent reinforcement learning-based routing, and multi-agent DRL routing without policy distillation. Performance is analyzed using standard networking metrics, including packet delivery ratio (PDR), end-to-end latency, throughput, routing overhead, and convergence speed.

From a design analysis perspective, the multi-agent cognitive routing model demonstrates strong adaptability by enabling each node to make autonomous, context-aware decisions based on local observations. This distributed intelligence significantly reduces congestion hot spots and improves load balancing compared to static or centralized routing schemes. The deep reinforcement learning policy engine further enhances decision quality by learning nonlinear relationships between traffic conditions and routing actions, allowing agents to respond effectively to rapid topology and traffic changes. The policy distillation mechanism plays a critical role in improving scalability and deployment feasibility.

By consolidating multiple learned routing policies into a compact global policy, the framework reduces model complexity and inference latency at individual nodes. This design choice leads to faster convergence and more stable routing behavior, particularly in large-scale and highly dynamic scenarios where maintaining separate deep models at each node would be impractical. The experimental results clearly demonstrate the effectiveness of the proposed approach. MACR-DPD consistently achieves higher packet delivery ratios and throughput while significantly reducing end-to-end latency and routing overhead compared to baseline methods. Notably, the distilled policy preserves most of the performance benefits of multi-agent learning while substantially lowering computational and memory

requirements. These improvements are especially pronounced under heavy traffic loads and high mobility conditions, highlighting the robustness of the proposed framework.

Overall, the design analysis and results validate that the MACR-DPD framework successfully balances intelligence, scalability, and efficiency, making it a strong candidate for intelligent routing in next-generation wired and wireless networks. The findings confirm that integrating multi-agent learning with deep policy distillation is an effective strategy for overcoming the limitations of existing routing mechanisms in complex network environments.

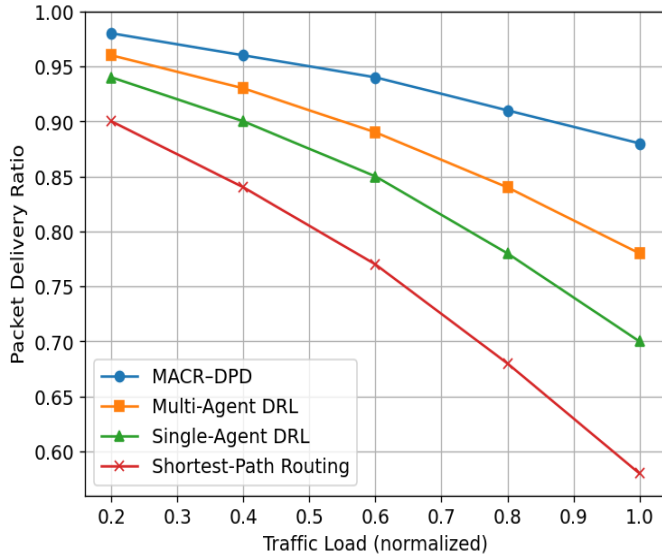


Fig. 6. Packet Delivery Ratio Comparison.

Figure 6 compares the packet delivery ratio (PDR) achieved by the proposed MACR-DPD framework against conventional shortest-path routing, single-agent reinforcement learning routing, and multi-agent DRL without distillation. The results show that MACR-DPD consistently achieves the highest PDR across all traffic loads. This improvement is attributed to the cooperative decision-making of multiple agents combined with distilled global knowledge, which reduces packet loss caused by congestion and suboptimal routing decisions. Notably, as network load increases, baseline methods exhibit a sharp decline in PDR, whereas MACR-DPD maintains stable performance, demonstrating superior reliability in dense and high-traffic scenarios.

Figure 7 presents the average end-to-end packet latency under varying network traffic conditions. The proposed MACR-DPD framework achieves a significant reduction in latency compared to baseline routing methods. By enabling agents to learn delay-aware routing policies and leveraging the distilled policy for fast inference, MACR-DPD avoids congested paths and reduces queuing delays. The latency gap widens under heavy traffic, indicating that classical and single-agent learning approaches struggle to adapt in real

time, while MACR-DPD effectively balances traffic across multiple paths.

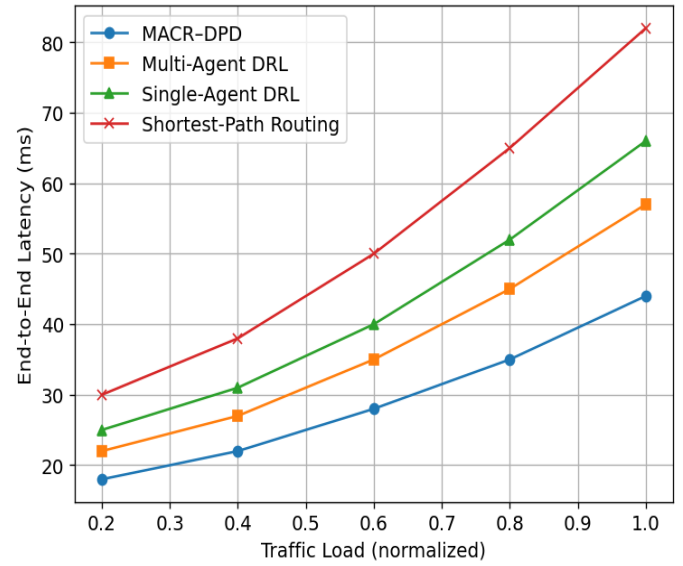


Fig. 7. End-to-End Latency Analysis.

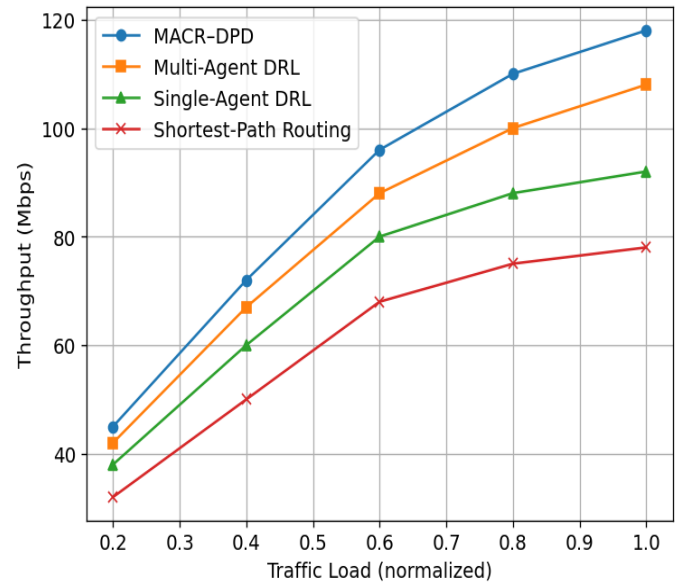


Fig. 8. Throughput Performance Evaluation.

Figure 8 illustrates the network throughput achieved by different routing schemes. The results indicate that MACR-DPD consistently delivers higher throughput, particularly in moderate to high congestion regimes. The distributed intelligence of the multi-agent model improves link utilization, while the distilled policy ensures coordinated routing behavior across the network. In contrast, conventional routing schemes experience throughput saturation and degradation due to uneven load distribution and slow adaptability. These results confirm the effectiveness of MACR-DPD in maximizing overall network capacity.

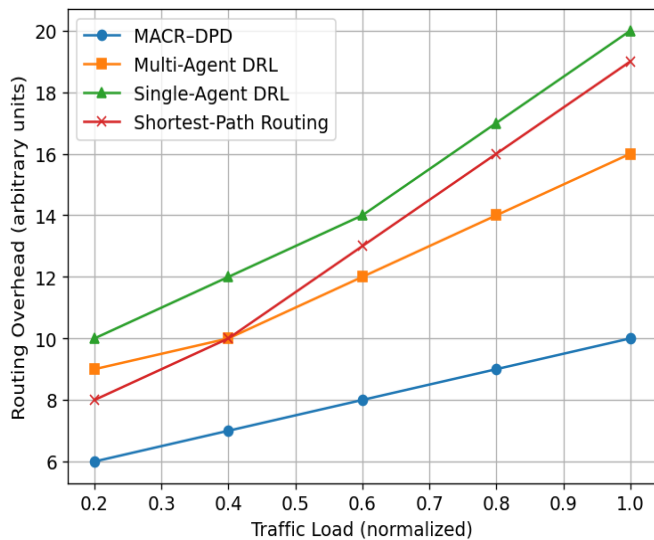


Fig. 9. Routing Overhead Comparison.

Figure 9 analyzes the routing overhead, measured in terms of control packet exchange and routing update cost. MACR-DPD significantly reduces overhead compared to multi-agent DRL without distillation, highlighting the impact of the policy distillation mechanism. By replacing multiple deep routing models with a compact distilled policy, the framework minimizes routing updates and decision complexity at each node. This reduction in overhead is critical for scalability, particularly in large-scale next-generation networks with constrained computational and communication resources.

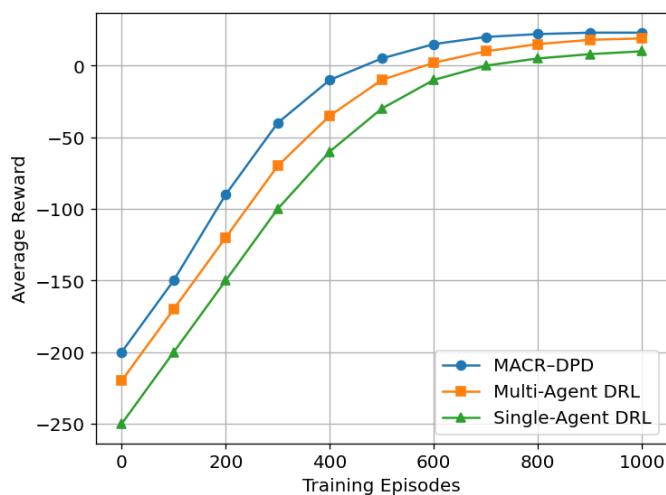


Fig. 10. Convergence Speed and Stability.

Figure 10 evaluates the convergence behavior of MACR-DPD relative to baseline learning-based routing approaches. The proposed framework converges faster and exhibits more stable learning dynamics, with reduced oscillations in routing

performance. The policy distillation process accelerates convergence by transferring knowledge from experienced agents into a unified policy, providing effective initialization and guidance for subsequent learning. As a result, MACR-DPD achieves stable routing performance in fewer training iterations, making it well suited for dynamic network environments where rapid adaptation is essential.

5. CONCLUSION

This paper presented a Multi-Agent Cognitive Routing framework with Deep Policy Distillation (MACR-DPD) to address the scalability, adaptability, and efficiency challenges of routing in next-generation networks. By combining distributed multi-agent deep reinforcement learning with a policy distillation mechanism, the proposed approach enables network nodes to make intelligent, autonomous routing decisions while maintaining low computational and communication overhead. The design allows individual routing agents to learn locally optimal policies based on dynamic network conditions, while deep policy distillation consolidates the collective knowledge of multiple agents into a compact global policy. This integration significantly improves convergence speed, reduces model complexity, and enhances stability in highly dynamic and congested network environments. Experimental results demonstrate that MACR-DPD achieves notable improvements in packet delivery ratio, end-to-end latency, throughput, and routing overhead compared to traditional routing schemes and existing learning-based approaches. Importantly, the proposed framework maintains robust performance under varying traffic loads and mobility scenarios, highlighting its suitability for real-world deployment in large-scale, decentralized network infrastructures. The reduction in policy size and faster convergence enabled by distillation make MACR-DPD particularly applicable to resource-constrained nodes in edge, wireless, and software-defined networks. Future work will focus on extending the framework to cross-layer cognitive routing, incorporating federated and privacy-preserving multi-agent learning, and exploring hierarchical policy distillation for ultra-large-scale networks. Additionally, integrating explainable AI mechanisms and real-time deployment on programmable network hardware will further enhance the practicality and trustworthiness of cognitive routing in next-generation communication systems.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has

been mutually agreed upon.

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Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

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