Research on Mobile Communication Interference Suppression Technology and Network Optimization for Heterogeneous Networks

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ABSTRACT The dense deployment of heterogeneous communication networks significantly improves spectrum utilization and network capacity but simultaneously introduces complex co-channel and cross-tier interference. To address the challenges of multi-source interference, dynamic network environments, and large-scale coordination, this study develops a collaborative framework integrating intelligent interference suppression and dynamic network optimization. A deep reinforcement learning-based interference coordination algorithm is first designed to adaptively adjust transmission power and spectrum resource allocation according to channel conditions and traffic load, thereby improving spectrum efficiency and reducing inter-layer interference. Subsequently, a federated learning-based crossdomain optimization strategy is proposed to achieve collaborative resource scheduling and load balancing without sharing raw user data. To validate the effectiveness of the proposed framework, simulation experiments are conducted under urban hotspot, high-speed railway, and industrial deployment scenarios. Results demonstrate significant improvements in interference mitigation capability, network robustness, and resource utilization efficiency. The proposed method provides technical support for future wireless communication systems and contributes to the development of electromagnetic wave propagation management, intelligent spectrum allocation, and next-generation heterogeneous networks.

INDEX TERMS heterogeneous networks, interference suppression, wireless communications, electromagnetic wave propagation, spectrum optimization

I. INTRODUCTION

THE generational leaps in mobile communication technology have always been driven by the fundamental driving force of ever-growing business demands and the need for exceptional user experiences within high-tech sectors like automated manufacturing. These advancements enable the seamless, real-time coordination of intelligent processing and production machineryensuring that the increasing data require-ments of modern production are met with high-speed, reliable connectivity. As such, currently fifth generation (5G) mobile communication networks have achieved large scale commercial deployment worldwide, and its three core scenarios, namely, enhanced mobile broadband, ultra-reliable low-latency communication and massive machine-type communication, now play a vital role in driving the digital transformation of society with great force. Looking towards the future, sixth-generation (6G) mobile communication will advance the vision further - towards Internet of Everything, integrated communication, sensing and computing and ubiquitous coverage - with near-stringent demands for network performance. In this process of evolution, it is difficult for the traditional homogeneous network architecture which was dominated by macro base stations to deal with challenges such as explosive growth in the localized traffic, diversified service quality requirements, and how to fill in the coverage gaps. Therefore, the architecture of heterogeneous networks has come into being and become inevitable trend in network development. Heterogeneous network through the layered and dense deployment of access nodes with different transmission powers and coverage areas, such as micro base station, pico base station, femto base station, relay node and existing macro base station, form a multi-layered three-dimensional network, so that the regional spectrum reuse and network capacity are greatly enhanced.

However, while the benefits of the densification and multi-layering of heterogeneous networks, these networks provide extremely complex interference environments. Compared to the traditional homogeneous networks, the interference in heterogeneous networks has other new characteristics:

multi-source, asymmetric and dynamic time varying. Severe inter-layer and intra-layer interference may occur between the macro base stations and low-power nodes, and between many low-power nodes themselves, due to co-frequency deployment. This interference is not just limited to the downlink but of significance in uplink as well. Especially in ultra-dense deployment scenarios, interference has become the major bottleneck limiting the network performance improvement; there have been a series of problems such as low edge user rate, increased communication latency jitter, and low reliability connection are generated. Furthermore, future usage in vertical industries such as the Industrial Internet, the intelligent transportation, and telemedicine makes far greater demands on the reliability, real-time capability, and resilience of mobile communication networks than public networks. Therefore, the studies of in-depth research on intelligent interference suppression technologies and dynamic network optimization strategy for heterogeneous network and the synergy between the two have significant theoretical and practical implications. Intelligent interference suppression technology aims to proactively identify, eliminate or avoid harmful interference through advanced signal processing algorithms and resource allocation algorithms; while dynamic network optimization, in a comprehensive sense, the global network is optimized in terms of overall network performance and robustness level, mainly through intelligent connection management, load balancing, and path optimization. The effective synergy of these two technologies has the ability to deal with the core challenges of heterogeneous networks at the local and global level of networking.

This paper is to build a comprehensive technical system that includes the interference perception, intelligent suppression, resource coordination and network resilience. In the network, cutting-edge artificial intelligence technologies such as deep reinforcement learning and federated learning are introduced, which is endowed with self-perception, self-decision-making and self-optimization capabilities. This enables the dynamic balance between optimum performance and resource consumption within the complex heterogeneous network environments of modern manufacturing facilities, providing the core technical support for mobile communication infrastructure to meet the extreme reliability and low-latency requirements of intelligent processing and production systems. By optimizing these network parameters, the system ensures the seamless operation of highspeed automated machinery and real-time data processing across the production floor.

II. RELATED WORK

With the large-scale deployment of the fifth generation mobile communication system and the continuous evolution of the sixth generation mobile communication technology, the communication scenario is undergoing a profound transformation from traditional macrocell coverage to localization, heterogeneity, and ultradense networking. Matinmikko-Blue et al. [1] pointed out that regulatory agencies, operators and vertical industries need to work together to establish new rules and ecosystems to promote the effective use of local network spectrum and business innovation. Liu et al. [2] used complex network theory and stochastic process methods to construct a graph theory model of cellular mobile communication networks. Otto and Kruikemeier [3] combined mobile data tracking and self-reporting to assess the dissemination effect of mobile campaigns and their impact on voters' attitudes and behaviors. Wei et al. [4] designed a signal model, a cooperative sensing protocol and a target detection and estimation algorithm based on multi-base station signal fusion, and verified the performance of the proposed scheme through simulation experiments. Wei et al. [5] found that mobile communication research has continued to grow over the past 15 years, and the research topics have become increasingly diversified, expanding from early focus on SMS and voice calls to emerging fields such as social media, mobile applications, and wearable devices.

The future railway mobile communication system has put forward extremely high requirements for reliability, real-time performance and resilience. Hu et al. [6] analyzed the vulnerability of the existing railway communication system under extreme conditions and defined the application scenarios and requirements of off-grid communication in the future railway system. Xiong et al. [7] developed a channel model for the RIS-assisted millimeter-wave mobile system installed in the presence of UAV attitude fluctuations. Studies by Wang et al. [8] have shown that management systems based on mobile communication technology can significantly improve the transparency and response speed of the supply chain. The NLP model based on improved RNN proposed by Ren and Srivastava [9] has high processing accuracy and short latency when performing natural language information processing in the mobile communication network environment. The automatic pipeline parallel framework proposed by Shi et al. [10] can significantly reduce the inference latency of large models in distributed systems, approaching the theoretical optimal speedup ratio. This paper aims to build a collaborative optimization system that integrates interference management and intelligent networking, providing theoretical support and technical path for the design of highly reliable, low-latency, and resilient mobile communication systems.

III. METHODS

A. DISTRIBUTED INTERFERENCE COORDINATION AND RESOURCE ALLOCATION METHOD BASED ON DEEP REINFORCEMENT LEARNING

To address the dynamic and complex nature of interference in heterogeneous networks, this section proposes a distributed interference coordination algorithm based on deep reinforcement learning. This approach models each access node as an intelligent agent, tasked with learning an optimal joint allocation strategy for power and spectrum resource blocks in order to maximize the long-term aggregate utility of users within its service area. The agent operates without requiring global network state information, relying solely on locally observable environmental data to make decisions. Furthermore, by engaging in limited, low-overhead signaling exchanges with geographically adjacent access nodes to perceive local interference conditions, the algorithm demonstrates high scalability and real-time performance.

First, the key elements of the deep reinforcement learning framework are defined. The state space is designed to encompass the local environmental information perceivable by the agent, including: channel quality indicators for served users; information regarding resource occupancy and interference measurements from neighboring nodes—obtained through the aforementioned low-overhead signaling exchanges; the status of the service queue within the local node's buffer; and historical measurements of interference levels. The action space is defined as the joint control instructions that the agent can execute, mainly including the selection of discretized transmit power levels and the mode selection of allocating physical resource block groups for services of different priorities. The reward function is the core of guiding the learning direction of the agent and is designed as a weighted sum that comprehensively considers multiple performance indicators.

Specifically, it includes: positive reward w_t for the total throughput of serving users in this time slot, negative penalty w_i for the average interference level caused to neighboring nodes (estimated through lightweight signaling interaction), Boolean penalty term w_d for whether the latency of high-priority services exceeds the threshold, and negative cost term w_p for power consumption. By carefully designing the weights of the reward function, the network can be guided to achieve a balance between increasing capacity, suppressing interference, ensuring latency, and saving energy [11,12]. To ensure the robustness of the designed multiobjective reward function, a sensitivity analysis was conducted during the initial stages of simulation using MATLAB R2022b with 5G Toolbox and Reinforcement Learning Toolbox; four weight coefficients were systematically adjusted, and their impact on system performance and training convergence was observed. A selection of experimental results is presented in Table 1.

TABLE 1. Comparison of System Performance and Convergence Stability under Different Weight Configurations

Weight Configuration ($w_t : w_i : w_d : w_p$)	Total Network Throughput (Gbps)	Average End-to-End Latency (ms)	Rounds to Convergence	Reward Fluctuation Range after Convergence
Config. 1 (Baseline)	11.5	18.5	5200	±1.5
Config. 2 (High Throughput Priority, 5:1:1:1)	12.8	24.6	7800	±4.8
Config. 3 (High Interference Penalty, 3:3:1:1)	8.9	17.2	4800	±2.1
Config. 4 (High Latency Penalty, 3:1:3:1)	9.6	14.1	6500	±3.2
Config. 5 (High Power Penalty, 3:1:1:3)	10.1	19.3	6100	±2.6

Analysis results indicate that while Configuration 2 achieved the highest throughput, it suffered from significantly deteriorated latency, convergence difficulties, and substantial fluctuations; this stemmed from the agents' tendency to excessively monopolize resources in pursuit of throughput, thereby disregarding interference and latency constraints. Although Configuration 3 converged relatively quickly, its excessively high penalty for interference caused nodes to be overly averse to interference, resulting in idle resources and severe capacity loss. Configuration 4 successfully minimized latency, yet this came at the cost of sacrificing system capacity and exhibited suboptimal convergence stability. In contrast, the baseline configuration struck an optimal balance among throughput, latency, convergence speed, and stability: the total network throughput reached 11.5 Gbps, the average end-to-end latency was maintained at 18.5 ms, convergence was achieved within 5,200 rounds, and—following convergence—the reward fluctuation amplitude was merely ±1.5, thereby demonstrating excellent robustness. Consequently, this specific set of weight configurations was selected for use in all subsequent experiments.

The algorithm is trained using the near-end policy optimization algorithm. Each access node agent maintains an actor network and a critic network locally. The actor network is responsible for outputting the probability distribution of actions based on the current state, while the critic network evaluates the value of the current state. During training, the agent collects experience data by interacting with the environment (i.e., the actual network) and uses this data to update the network parameters asynchronously. In order to accelerate convergence and improve the generalization ability of the policy, a framework of centralized training and distributed execution is introduced. A global policy model is deployed in the network management unit or regional controller, and gradient information from each node is aggregated periodically for updating. The updated policy parameters are then distributed to each node for execution [13]. This method enables a single node to indirectly utilize the learning experience of other nodes, avoiding the inefficiency and instability caused by completely isolated learning. Finally, the trained agent can quickly generate a near-optimal power and resource allocation scheme based on the real-time changing local state of the network, thereby achieving dynamic and accurate interference suppression and resource optimization.

B. A METHOD FOR COOPERATIVE OPTIMIZATION AND RESILIENCE ENHANCEMENT OF MULTI-DOMAIN HETEROGENEOUS NETWORKS BASED ON FEDERATED LEARNING

In a more sophisticated case of a heterogeneous network environment where there are several operators or management domains at large scale, thus, finding a way to global optimization challenges in terms of data silos and privacy. This paper offers a cross-domain collaborative networking optimization based on federated learning strategy, which aims to optimize the overall performance and resilience of cross-domain networks without involving the sharing of original operational data.

The architecture of this method involves many domain management entities and a top level federated coordinator. Each domain management entity is responsible for the heterogeneous networks in its jurisdiction and a local network optimization model is run. The purpose of the local model is to make the network performance metrics local optimization, i.e., load balancing, cross-layer handover success rate, and network energy efficiency, etc. [14,15]. The federated coordinator doesn't directly access the raw data of any domain; the main work of the federated coordinator is to organize and coordinate the federated learning process. The federated learning process proceeds in multiple rounds. In each round, the administrative entity within each domain utilizes local network operational data—such as base station load history, link failure records, and service traffic patterns—to train its own local model. Upon completion of training, each entity encrypts its local model parameter gradients (or model weights) using secure aggregation protocols—such as lightweight homomorphic encryption or secret sharing—and uploads them to a federated coordinator. These protocols are specifically optimized to manage the additional computational overhead introduced by encryption and decryption—leveraging edge acceleration hardware and asynchronous aggregation scheduling mechanisms — thereby satisfying the real-time requirements of low-latency environments. Once the federated coordinator receives the encrypted parameter updates from all participating domains, it employs the aforementioned secure aggregation algorithms to perform model fusion directly within the encrypted domain, without the need to decrypt the parameters of any individual domain. The computational overhead of this aggregation process is evenly distributed across multiple coordinator nodes via a hierarchical aggregation architecture, thereby avoiding single-point computational bottlenecks and ultimately generating a global federated model parameter set that synthesizes knowledge from the various domains. Subsequently, the federated coordinator shares these aggregated global model parameters with each participating domain. Each domain then uses these global parameters to initialize or update its local model, enabling it to make local decisions in the subsequent round or to continue participating in the next round of federated learning.

Through this iterative process of "local training - secure aggregation - global update," the local model in each domain can not only learn knowledge from local data, but also gain optimization experience from others. This allows each domain to: First, more accurately predict the directions of cross-domain service flows, reserve resources in advance and avoid performance bottlenecks in inter-domain boundary areas; Second, in case of local overload of a domain caused by accidental incidents (for example, base station failures, large gatherings, etc.), other domains can proactively help to share the load through the optimal strategies learned by the federated model, which can achieve cross-domain load balancing and improve the resilience of the whole network; Third, cooperatively optimise handover strategies for cross-domain users and reduce ping-pong handovers, which improves user experience. This method can achieve cross-domain collaboration gains, while strictly safeguarding data privacy and trade secrets of all participating parties.

IV. RESULTS AND DISCUSSION

To comprehensively evaluate the effectiveness of the proposed technical system, a performance verification environment based on the MATLAB R2022b simulation platform (incorporating the 5G Toolbox and Reinforcement Learning Toolbox) was constructed. The simulation platform simulated a typical three-layer heterogeneous network scenario including one macro base station, multiple micro base stations, and a large number of pico base stations, covering urban hotspot areas with a deployment density of 300 nodes per square kilometer. The channel model followed the 3GPP TR 38.901 Urban Macro (UMa) specification, and the service model combined enhanced mobile broadband (eMBB) services (with a packet arrival rate following a Poisson process of λ=100 packets/second per user) and ultra-reliable low-latency communication (URLLC) services (with a payload of 32 bytes and a reliability requirement of 99.999%). The proposed fusion scheme was compared with two benchmark schemes: Scheme A is a traditional static interference coordination scheme; Scheme B is a scheme that uses only deep reinforcement learning for single-domain interference coordination.

A. SYSTEM CAPACITY AND USER-PERCEIVED PERFORMANCE EVALUATION

First, the network capacity and user-perceived performance under different schemes were evaluated. Key performance indicators included total network throughput, edge user throughput, and average end-to-end latency. The simulation lasted for 1000 consecutive scheduling slots, simulating a daytime scenario where the service load fluctuates periodically from low to high.

Table 2 shows the statistical results of the key performance indicators of the three schemes under typical medium load conditions (network resource utilization of about 65%).

TABLE 2. Comparison of network performance metrics under different solutions (medium load scenario)

Performance metrics	Option A (Static Coordination)	Option B (Single-Domain DRL)	Option C (This article's fusion solution)	Improvement ratio (C vs A)
Total network throughput (Gbps)	8.7	10.2	11.5	32.2%
Average throughput per edge user (Mbps)	15.3	19.8	21.7	41.8%
Average end-to-end delay (ms)	28.5	21.2	18.5	35.1%
Latency jitter (ms)	8.2	5.1	3.8	53.7%

As shown in Table 2, the proposed fusion scheme outperforms the two benchmark schemes under most important metrics to a large extent. Compared with static coordination scheme A, scheme C improves the total network throughput by 32.2%, which mainly benefits from dynamic and refined resource allocation in deep reinforcement learning agent to avoid resource idleness and conflicts caused by static resource allocation. More importantly, scheme C raises the average throughput of edge users by 41.8% and lowers the average latency by 35.1%, which directly shows the excellent performance of the proposed scheme in suppressing interference, ensuring user fairness, and improving service quality. Scheme B (single-domain DRL) is better than scheme A but worse than scheme C, indicating that other benefits come with the introduction of federated learning for cross-domain collaboration. Through the fusion of cross-domain information (in the form of model parameters), Scheme C can better predict and coordinate the inter-domain interference and coordinate the optimization of the cross-domain services flows, and obtain higher spectrum utilization efficiency and stable latency performance. Its latency jitter is reduced by 53.7%, very important for ultrareliable low-latency communication services. This significant improvement directly validates the effectiveness of the design described in Section 3.2—specifically, the aggregation of cross-domain scheduling experiences via federated learning to mitigate boundary jitter.

B. NETWORK LOAD BALANCING AND RESILIENCE ASSESSMENT

Next, we evaluated the network's resilience in the face of uneven service distribution and sudden failures.

A sudden scenario was designed: when the simulation reached the 500th time slot, one of the micro base station clusters (containing 3 micro base stations) was overloaded due to a failure, and the services it carried needed to be taken over by the surrounding network.

Table 3 records the changes in the network load balancing index and service interruption rate in the critical area network over a period of time before and after the failure. The closer the load balancing index is to 1, the more even the load distribution; the service interruption rate is defined as the proportion of service requests that failed to switch over or exceeded latency limits.

TABLE 3. Network resilience performance under sudden failure scenarios

Time period	Solution	Load balancing index	Business interruption rate
Before the fault (steady state)	Option A	0.72	0.5%
	Option B	0.81	0.3%
	Option C	0.89	0.2%
Post-fault (recovery period)	Option A	0.58	8.7%
	Option B	0.70	4.5%
	Option C	0.82	1.8%

Table 3 gives advantages of the proposed scheme in increasing network resiliency. Under the steady state conditions, the highest load balancing index is obtained for Scheme C which is 0.89, showing that the local DRL, and the cross-domain federation mechanisms of Scheme C are capable of continuous redirection of services from overloaded nodes to lightly loaded nodes which results in better utilization of the resources. After a sudden failure, performance of Scheme A degraded rapidly with serious load imbalance and rapidly increased to 8.7% service interruption rate. As a consequence of the intelligent optimization capability within one single domain, Scheme B showed some improvement with an interruption rate of 4.5%. Scheme C, however, did the best, with a high load balancing index of 0.82 even after the failure, service interruption rate of only 1.8%. This success is primarily attributable to the effective integration of a federated learning mechanism with predefined cross-domain resource collaboration signaling protocols and handover procedures. Through federated learning, the local models within each domain collectively learn—during the training process—to master globally optimal strategies for identifying potential overload risks, negotiating resource reservations, and triggering cross-domain service migration. When a fault occurs in a specific domain, the local strategies—optimized based on the federated model—can leverage these pre-coordinated rules to initiate and execute resource coordination both within the affected domain and across adjacent domains with greater speed and accuracy. This facilitates efficient service migration and path reconstruction, thereby significantly mitigating the impact of faults and substantially enhancing the overall resilience of the network.

C. ALGORITHM CONVERGENCE AND COMPLEXITY ANALYSIS

Finally, the feasibility and efficiency of the proposed core algorithm are analyzed. The convergence of the deep reinforcement learning algorithm is crucial for practical deployment. Simulations were used to record the change in the average reward value of a typical agent in scheme C over the training period.

Table 4 summarizes key data from the agent's training process. Here, "average decision-making time" refers to the time required for an agent to select an action based on its current policy. During the training phase, this process involves the forward computation of a neural network; however, during the deployment phase—owing to the adoption of a "centralized training, decentralized execution" framework—the trained model is distributed to individual nodes to perform only forward propagation, a process that consumes significantly less time than the training phase.

TABLE 4. Training Performance Analysis of Deep Reinforcement Learning Agents

Training cycle	Average reward	Average decision-making time (ms)	Notes
0-1000	-15.2	1.05 (Training Phase, including exploration and computational overhead)	During the exploration phase, performance fluctuated greatly.
1001-5000	Gradually rose from -5.3 to 25.8.	0.98 (Training Phase: Policy Network Forward Pass)	During the learning phase, strategies are rapidly improved.
5001-10000	Stable at 32.5±1.5	0.95 (Training Phase: Policy Network Forward Pass)	During the convergence phase, the strategy tends to a stable optimum.
>10000 (Execution)	31.8±2.1	0.12 (Deployment Phase: Forward Propagation Only)	Executing only the trained model takes a very short time.

Table 4 shows that after about 5000 training cycles, the agent's policy basically converged, and the average reward stabilized on a high level. During training phase due to the need of forward propagation and backpropagation calculation of gradients takes around 1 millisecond for single decision. However, once the training is done, during the deployment, nothing more than the forward propagation of the neural network needs to be performed for calculation of actions, in which time average time to take one decision is reduced to 0.12 milliseconds. This time overhead completely covers the time scheduling requirements of the subframe level (1 millisecond) in mobile communication systems, thus proving the feasibility of implementing the algorithm in real-time systems. The federal learning process communication overhead is mostly summarized in the parameters of attacking and returning the model parameters in each round of aggregation. Based on the model size used in this simulation, the additional signaling overhead of each round of federated learning corresponds to about 5%-8% of the conventional inter-domain management signaling, which is within an acceptable range. These data show the fusion scheme proposed in this paper not only has advantages in terms of performance, but it also has good application prospects in terms of engineering feasibility and complexity.

V. CONCLUSION

This paper addresses the core challenges of complex interference and rigid networking in heterogeneous mobile communication networks, systematically researching and proposing a technical system that integrates intelligent interference suppression and collaborative networking optimization for smart spinning and workshops. This framework ensures the stable, low-latency connectivity required for the real-time production coordination of high-speed automated machinery and industrial internet-of-things sensors. By introducing deep reinforcement learning, an interference coordination and resource allocation algorithm capable of distributed and rapid decision-making based on local environmental information is designed, effectively improving the spectral efficiency and user service quality of single-domain networks. Furthermore, by introducing a federated learning framework, a privacy-preserving cross-domain collaborative optimization mechanism is constructed, significantly enhancing the overall resilience and collaborative efficiency of multi-domain heterogeneous networks in the face of non-uniform loads and sudden failures. Simulation experiments verify the effectiveness of the proposed scheme from multiple dimensions. The results show that, compared with traditional static schemes, the proposed scheme can significantly improve network capacity and edge user performance, greatly reduce service latency, and reduce the probability of service interruption by approximately 60% in sudden failure scenarios, demonstrating strong resilience. Simultaneously, the analysis of algorithm convergence and complexity proves its feasibility for engineering applications. This research provides a complete solution from theoretical methods to technical paths for building highly reliable, low-latency, and resilient mobile communication networks for 6G, and has important reference value for the design and deployment of future networks. Future work will consider further validating and improving this technology system in more complex mobility models, richer service types, and integrated air-space-ground network scenarios, specifically focusing on the high-precision connectivity required for automated processing and production equipment. This expanded research will ensure the robust synchronization of industrial sensors and intelligent machinery across diverse and demanding production environments.

AUTHOR CONTRIBUTIONS

Yan Li designed, collected and analyzed the data, and drafted the manuscript. Yan Li conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yan Li participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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