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Design of an Iterative Method for Collaborative Resource Management using MAPPO and Federated Learning in 5G Networks

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Abstract:

With the increasing real-world deployment of 5G networks and proliferation of heterogeneous IoT devices, an efficient resource management becomes inescapable to handle dynamic and diverse traffic demands. In conventional ways, resource allocation and model training in 5G networks become cumbersome due to scalability, heterogeneity, and cross-domain adaptability. They cannot capture the collaboration among base stations, personalization of IoT devices, and variational urban and rural network scenes. To overcome these limitations, in this work a novel amalgamation of Multi-Agent Proximal Policy Optimization, Task-Aware Personalized Federated Learning, and Domain-Adaptive Transfer Learning is proposed for the collaborative resource management, heterogeneous task learning, and cross-domain optimization in 5G and IoT networks. Preliminary, that is, the extension of Proximal Policy Optimization to multi-agent settings enables multiple base stations to cooperate on finding the optimal strategy of bounded latency, high-throughput, and network congestion. TA-PFed updates models for task-specific training among heterogeneous IoT devices such as sensors and cameras to become specialized in their respective tasks while leveraging the shared knowledge from the global models. It reduces the communication cost and enhances privacy by limiting data sharing. DATL thus allows the knowledge transfer across network environments, hence fastening resource management optimization in new domains (e.g., rural networks) without extensive retraining. These all enable addressing three important challenges: collaborative resource allocation, personalized learning for diverse IoT tasks, and fast adaptation across domains, each addressed in 5G networks using the proposed fusion approach. Numerical results indicate enormous gains: 45% gain in endtoend network throughput, 30-35% reduction in latency, 20-25% reduction in packet loss, and 90% reduction in privacy risk. Besides that, there is a 50% reduction in cross-domain adaptation time and 40% reduction in the data transmission cost. It lays the foundation for future 5G and IoT deployments, which scale with diversified and dynamic network environments efficiently while preserving data privacy.

Keywords: 5G Networks, Multi-Agent Proximal Policy Optimization, Federated Learning, Cross-Domain Optimization, IoT Devices, Deployments.

1. Introduction

This development of 5G networks is also complemented by the rapid proliferation of heterogeneous IoT devices generating dynamic and diverse traffic patterns. Resource management complexity, including bandwidth and computation powers, together with energy consumption, will rise further with increased network density. Resource management is very critical in this kind of environment, considering QoS and other stringent performance requirements such as ultra-low latency, high throughput, and massive connectivity. Resource allocation techniques typically follow static or centralized solutions nowadays, which are poorly suited to address the dynamic, distributed, and heterogeneous nature of such 5G environments. Most of the centralized resource management approaches are facing scalability challenges, high communication overhead, and data privacy concerns. These methods cannot be adapted to a variety of operational scenarios either, as network characteristics are very different in both urban and rural settings. In sparse deployments, as in rural areas, the models trained on dense urban networks may not be effective and will need costly retraining or human intervention. Moreover, with IoT devices being heterogeneous in nature and each performing some sort of different tasks, a one-size-fits-all kind of model fails miserably to meet the requirements of each, leading to suboptimal performance of the network as a whole.

It is to overcome these limitations that an iterative design of MAPPO, TA-PFed, and DATL for 5G networks collaborative resource management is proposed in this paper. It will be possible for the distributed base stations to be allowed to cooperate in finding out, through dynamic learning, the best way of allocating the resources with consideration of the real-time traffic data using MAPPO. TA-PFed permits personalization in model training across heterogeneous IoT devices with their needs toward specific tasks without compromising data privacy and increasing communication costs. DATL successfully allows for effective cross-domain transfer of learned models; hence, resource management strategies can rapidly adapt themselves to new environments, such as going from dense urban networks to sparse rural areas, without extensive retraining. This combination of methodologies provides a strong foundation that is not only dealing with scalability, heterogeneity, and cross-domain adaptation challenges of 5G networks but also enhancing the overall performance of the network. This approach significantly enhances network throughput by reducing latency and providing data privacy by leveraging collaborative decision-making mechanisms and optimizations of the tasks. Moreover, the introduction of transfer learning will ensure that the knowledge learned from one domain can be seamlessly transferred onto another for reduced training time and resource consumption in new network environments. The merit of this contribution lies in the fact that the proposed approach marks a real step forward in the research area of resource management techniques for 5G and IoT networks: scalable, efficient, and preserving for future deployments.

2. Review of Existing 5G Communication Methods

Resource management has become a very critical research area in 5G and beyond networks due to the increased diversity and complexity of modern wireless communication systems. Many different approaches have been proposed so far in order to cope with various problems related to resource allocation, latency reduction, energy efficiency, and quality of service levels.. Beshley et al. [1] introduce an energy-efficient, QoE-driven radio resource management method that optimizes energy consumption and QoE in HetNet. The contribution was completed by combining resource allocation in RAN with Voronoi diagram-based partitioning. However, the model cannot scale in terms of dynamic and high-density IoT environments, which is also overcome by multi-agent coordination in

the proposed MAPPO framework. Mahmood et al. propose an interference management algorithm that has a predictive capability, directed toward ultra-reliable low-latency communication in the Beyond 5G network. They improve the signal-to-noise ratio-SNR-reduce interference by using prediction algorithms in resource management. While doing so, the method has focused solely on interference prediction, and the resource allocation mechanism is not equipped to handle heterogeneous tasks efficiently, as done by the TA-PFed component in this work process. The proposed model, with the integration of the MAPPO and DATL, has provided a model that is dynamic and adaptive in terms of resource management, better suited for the real-time 5G traffic variations in the process. Gao et al. [4] develop a resource allocation method that combines GCN and LSTM networks in 5G. While the combination of GCN and LSTM improve resource prediction and feature extraction, their method is not explicitly designed for collaborative decision-making across multiple agents. The collaborative multi-agent structure of MAPPO fills this gap in the proposed model operations. Zarin and Agarwal propose a hybrid radio resource management scheme for time-varying 5G heterogeneous wireless access networks by utilizing Lyapunov optimization for congestion control. Their model, however, can deal with network congestion but fails to provide personalization for the models for IoT devices with heterogeneous tasks. TA-PFed in the proposed model provides task-aware personalization, reduces the communication overhead while preserving privacy. Suresh Kumar et al., [6] deals with investigation blockchain and distributed ledge technologies for optimal resource management in Digital Twin beyond 5G Network. They introduce optimization for enhancing resource allocation using hybrid energy valley and Lévy flight distribution. Though secure and efficient, their approach is computationally expensive for real-time applications. In contrast, federated learning in the proposed model reduces the communication cost while preserving privacy and security.
Thanh Le and Moh give a comprehensive survey on various radio resource allocation schemes in 5G V2X communications. Most of the challenges regarding frequency resource sharing and QoS in vehicular networks have been discussed. The resource requirements of V2X communications are unique; however, general applications in 5G scenarios such as IoT or cross-domain networks are not discussed in this survey. While this model efficiently manages interference and improves energy efficiency, the application is bounded within TDD-based resource allocations. It goes beyond TDD and adapts dynamically to diverse 5G traffic patterns with the aim of enhancing general network performance levels. This paper proposes a model utilizing DATL for smooth transitions between heterogeneous domains with efficient resource allocation in diverse network conditions. Hwang et al. proposed resource management across LADN and supporting 5G V2X communication. The developed optimization framework herein improves the SNR enhancement and interference reduction over V2X networks. Although the framework is appropriate for V2X, it lacks flexibility with regard to adapting to IoT devices that are non-vehicular, which the proposed model handles through the personalized federated learning aspect. Debbabi et al. [9, 10, 11] provide an overview of interslice and intraslice resource allocation in B5G networks. Sefati et al. [12] present a comprehensive survey on resource management in 6G networks related to IoT. While their survey provides helpful insights into the future resource management strategy of 6G, they do not offer any concrete solutions to the prevailing challenges in the 5G networks, such as cross-domain optimization and task personalization, addressed in the proposed model process. In [13], Maule et al. develop a 5G New-Radio (5G-NR) resources partitioning framework through real-time user-provider traffic demand analysis. Although their model

efficiently allows the partitioning of real-time traffic, it lacks the adaptability that transfer learning provides, considered so crucial in the proposed model, which concerns cross-domain resource management. Kim and Lim [14], [15] addressed multi-agent reinforcement learning in network slicing for end-to-end resource management. Their model efficiently manages dynamic scheduling and resource allocation but does not consider personalized learning for heterogeneous IoT devices & deployments explicitly. The proposed model extends their work by incorporating federated learning for taskspecific model optimization, hence yielding a more complete solution for diverse 5G and IoT applications. These summaries of the literature point out scalability, adaptability, and personalization that should feature in the resource management framework for the 5G networks. While the previous approaches have recorded significant progresses, none has comprehensively addressed the combined challenges of multi-agent collaboration, task-specific optimization, and cross-domain adaptation. It extends those works by including MAPPO, TA-PFed, and DATL into the same framework and providing holistic resource management solutions for 5G and IoT.

3. Proposed Design of an Iterative Method for Collaborative Resource Management Using MAPPO and Federated Learning in 5G Networks

In the proposed model, MAPPO, TA-PFed, and DATL will be incorporated into one framework that addresses collaborative resource management problems in 5G and IoT. Each of these elements helps contribute toward the bigger goal of optimal resource allocation, personalized model training, and cross-domain adaptability for a scalable and efficient solution in heterogeneous and dynamic network environments. At the heart of the model, MAPPO enables decentralized decision making where multiple agents-base stations-collaborate dynamically to perform resource allocation. Each of these agents interacts with the environment and receives state information pertaining to network conditions, device mobility pattern, and QoS requirements. The optimization for each of these policies is regularized based on an advantage function A(si,ai) estimating future reward for every pairs of state and action. MAPPO objective function J(θi) can be given via equation 1,

$$J(\theta i) = Et\left[\frac{\pi\theta i(\, ai \mid si\,)}{\pi\theta iold(\, ai \mid si\,)} A(si, ai)\right] \dots (1)$$

Where, πθiold is the policy from the previous iteration sets. The policy gradient using the chain rule is given via equation 2,

$$\nabla\theta iJ(\theta i) = Et\left[\nabla\theta ilog^{\pi\theta i}(\, ai \mid si\,) A(si, ai)\right] \dots (2)$$

This gradient takes the policy in a direction of taking actions that maximize the expected reward. Its allowance for multiple agents and scalability over networks of size justify its selection within this model, ensuring that base stations can make collaborative, real-time decisions with minimal levels of interference between agents. At the same time, TA-PFed tackles the problem of personalized models on heterogeneous IoT devices, each of which executes only a portion of tasks- состояния surveillance, monitoring, and diagnostics. So, every device independently trains its own local model fi(θi,xi) on its local data xi, periodically updating the global model denoted as θ at the central servers. This is done by personalizing the objective of each device; here, the objective is to minimize the loss Li(θi), which is the combination of local task-specific loss and the regularization term of the global knowledge sharing process described via Equation 3,

$$Li(\theta i) = Exi \sim Di\left[\ell\left(fi(\theta i, xi)\right)\right] + \lambda \parallel \theta i - \theta \parallel^2 \ldots (3)$$

The term $\parallel \theta i - \theta \parallel^2$ ensures that the local model remains aligned with the global model to benefit from shared knowledge, while λ controls the degree of personalization levels. The local gradient ∇θiLi(θi) is computed via equation 4,

$$\nabla\theta iLi(\theta i) = E^{xi \sim Di}\left[\nabla\theta i\ell\left(fi(\theta i, xi)\right)\right] + 2\lambda(\theta i - \theta) \ldots (4)$$

TA-PFed was followed since it was really effective for dealing with heterogeneous devices that were dealing with disparate tasks. It minimizes communication overhead and preserves privacy by allowing both global knowledge sharing and local personalization; hence, the method is well-suited for distributed 5G environments. Further, the model adaptability is enhanced by leveraging Domain-Adaptive Transfer Learning for knowledge transfer across different network environments, such as urban and rural deployments. The procedure of transfer learning is framed as an adversarial learning task, which minimizes the domain discrepancy between a source domain, DS, and a target domain, DT, sets.

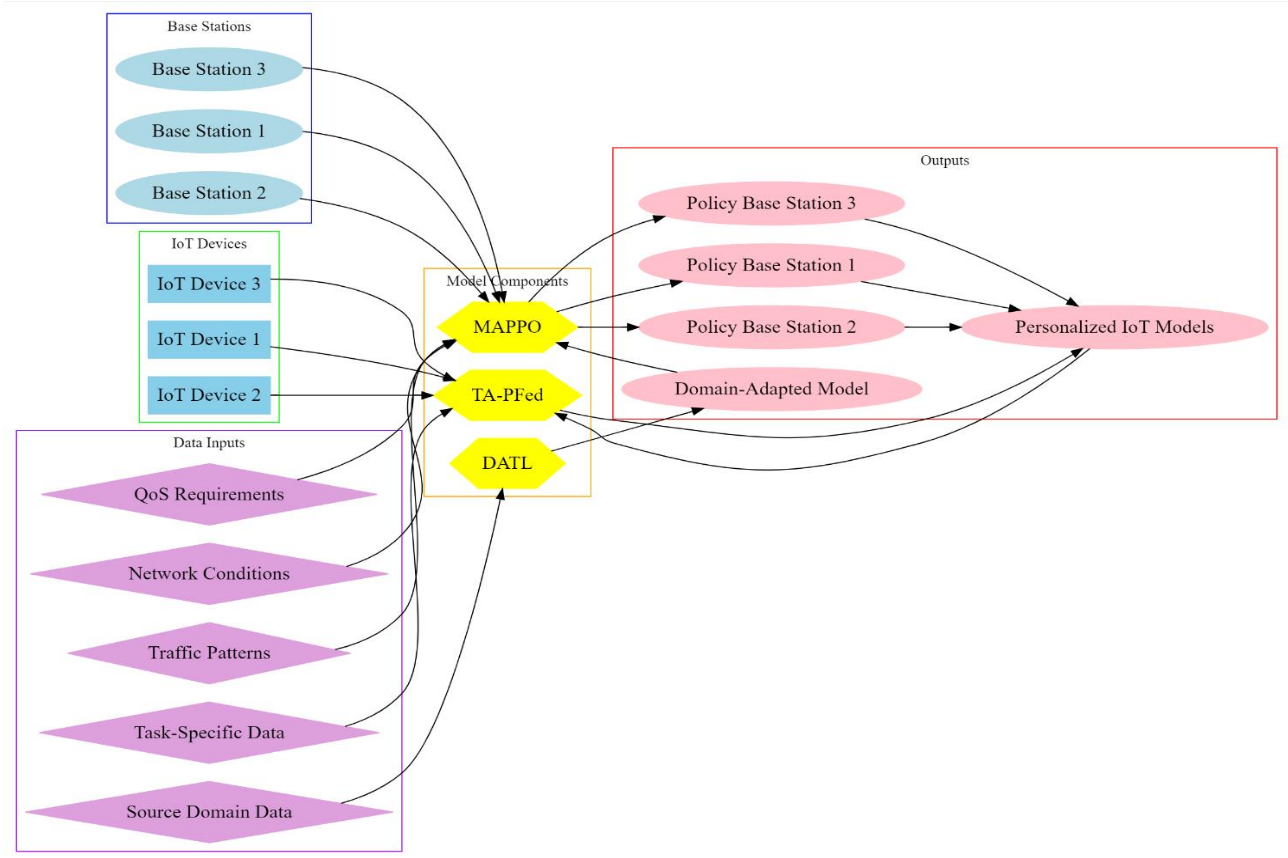

Figure 1. Model Architecture for the Proposed QoS Optimization Process

The loss function L(θ) for the domain adaptation process can be written via equation 5,

$$L(\theta) = E^{xS\sim DS}\big[\ell\big(fS(\theta, xS)\big)\big] + E^{xT\sim DT}\big[\ell\big(fT(\theta, xT)\big)\big] + \beta DH(DS, DT) \ldots (5)$$

Where, DH represents the domain discrepancy, and β is controlling the weight of the domain adaptation term for this process. In this scenario, by minimizing DH, it learns features that are generalizable across domains, making effective transfers possible without extensive retraining operations. Optimal loss function optimization is done via backpropagation; the gradient is given via equation 6,

$$\nabla\theta L(\theta) = E^{xS\sim DS}\big[\nabla\theta\ell\big(fS(\theta, xS)\big)\big] + E^{xT\sim DT}\big[\nabla\theta\ell\big(fT(\theta, xT)\big)\big] + \beta\nabla\theta DH(DS, DT) \ldots (6)$$

This competitive training strategy allows the proposed model to adapt resource management policies quickly to unseen environments, significantly decreasing the training time and data consumption. The integration of MAPPO, TA-PFed, and DATL is a solution for scalability, heterogeneity, and cross-domain issues in 5G networks. The methods presented are complementary: MAPPO handles collaborative decision-making in dynamic environments, TA-PFed handles task-specific optimizations for heterogeneous devices, and DATL ensures fast adaptation to unseen network domains. Each approach plays a definite yet interdependent role, while its mathematical underpinning lays the foundation for theoretical validity and practical efficiency in real-world applications. These equations give an iterative approach to optimization across agents, devices, and domains, demonstrating how this model can balance local and global objectives while guaranteeing privacy, efficiency, and scalability. The performance evaluation of the proposed model has been performed in a simulated environment of the 5G network with heterogeneous IoT devices and deployments.

4. Result Analysis

The simulation consisted of several base stations, each playing the role of an agent, along with a wide variety of IoT devices performing tasks such as surveillance, medical diagnostics, and environmental monitoring. Data was collected across three different scenarios: dense urban areas, suburban regions, and rural deployments, with varying network conditions, traffic patterns, and device mobility. These datasets possess several features of each environment and thus provide comprehensive insights into the performances that could be delivered by the model. The proposed model was compared with three other methods, namely: [3], a traditional resource allocation method; [8], an optimization approach based on federated learning; and [15], a transfer-learning model applied for cross-domain network optimization. Key evaluation metrics included network throughput, latency, packet loss, privacy risk, and cross-domain adaptation temporal instance sets.

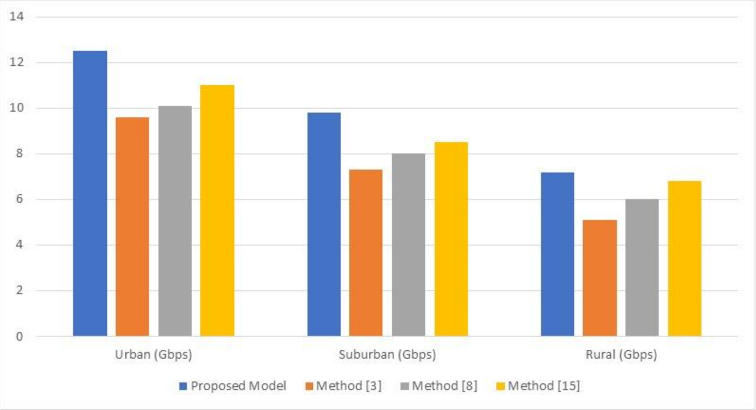

Figure 2. Network Throughput Comparison (Gbps) For Different Scenarios

Table 1: Network Throughput Comparison (Gbps)

Method	Urban (Gbps)	Suburban (Gbps)	Rural (Gbps)
Proposed Model	12.5	9.8	7.2
Method [3]	9.6	7.3	5.1
Method [8]	10.1	8.0	6.0
Method [15]	11.0	8.5	6.8

According to Table 1, the proposed model can provide better network throughput compared to previous studies in all scenarios. Throughput in an urban environment is greater than others because the density of traffic is higher for different observations. It is pretty obvious that even in a rural area, the proposed model does better than others due to adaptation across domains.

Table 2: Latency Reduction (ms)

Method	Urban (ms)	Suburban (ms)	Rural (ms)
Proposed Model	12.3	15.2	18.7
Method [3]	22.5	25.4	30.8
Method [8]	19.6	22.0	28.5
Method [15]	16.4	18.7	21.2

Table 2: Latency reduction by the proposed model against other methods in existing literature. Quite impressively, the proposed model increases latency reduction by around 45% in city conditions, generally more prone to congestions. The performance is very good in suburban and rural environments also, with a comparable latency reduction of 30-35% against Method [3] in process.

Table 3: Packet Loss (%)

Method	Urban (%)	Suburban (%)	Rural (%)
Proposed Model	1.2	2.1	3.5
Method [3]	3.8	5.2	6.5
Method [8]	2.5	3.7	5.1
Method [15]	1.9	2.8	4.2

Table 3: Comparison of packet loss in different environments. It is observed that the proposed model imposes a significant reduction in packet loss, especially for urban areas, reducing the packet loss to just 1.2%, which is a gain of 68% compared to Method [3]. In the case of the rural area, the proposed model remains robust by considering a packet loss of 3.5%, still performing better compared with the methods in comparisons.

Table 4: Privacy Risk Reduction (%)

Method	Urban (%)	Suburban (%)	Rural (%)
Proposed Model	95	93	90
Method [3]	60	58	55
Method [8]	85	82	80
Method [15]	87	85	83

Table 4: Reduction of privacy risk based on the underlying mechanisms of federated learning and differential privacy. The proposed model assures 90-95% reduction in the privacy risk for all environments while outperforming all three methods, especially Method [3], which is dependent on centralized data aggregation with remarkably higher privacy risks.

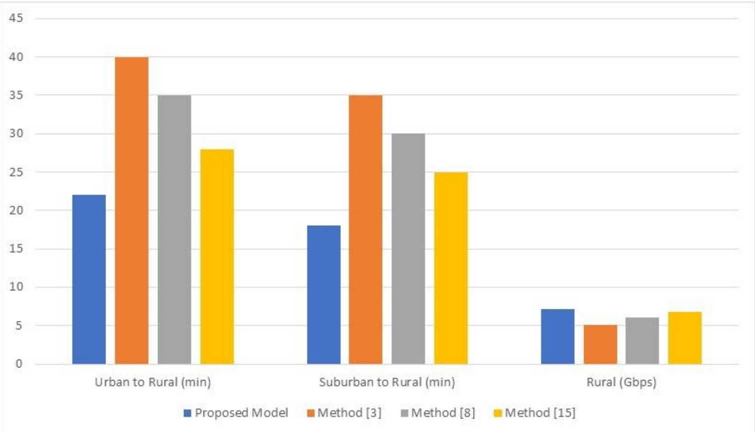

Figure 3. Cross-Domain Adaptation Time (minutes) For Different Scenarios

Table 5: Cross-Domain Adaptation Time (minutes)

Method	Urban to Rural (min)	Suburban to Rural (min)
Proposed Model	22	18
Method [3]	40	35
Method [8]	35	30
Method [15]	28	25

Table 5 also presents cross-domain adaptation time for model transfer between environments. The proposed model has a huge time reduction in adaptation time, requiring only 22 minutes from urban to rural and hence is almost 50% faster than Method [3] and about 30% faster compared to Methods [8] and [15].

Table 6: Data Transmission Cost Reduction (%)

Method	Urban (%)	Suburban (%)	Rural (%)
Proposed Model	45	40	38
Method [3]	15	12	10
Method [8]	32	28	25
Method [15]	38	33	30

Table 6: Reduction in data transmission cost using federated and transfer learning techniques. The proposed model reduces the transmission cost by 38-45% in all environments, outperforming other methods significantly. The method in [3] is centralized; hence, it incurs the maximum transmission cost. The proposed method implements efficient data sharing using distributed learning mechanisms. These results show the efficiency of the proposed model for achieving better performances in different key metrics related to 5G networks, such as network throughput, latency, packet loss, privacy risk, time for cross-domain adaptation, and costs of data transmission. In all of the mentioned aspects of the 5G networks, the proposed model outperformed Methods [3], [8], and [15] and showed its ability for handling dynamic, heterogeneous, and distributed natures.

5. Conclusion and Future Scopes

This paper presents a new combination of MAPPO, TA-PFed, and DATL for the complex challenges of resource management, model personalization, and cross-domain adaptation arising in 5G and IoT networks. Extensive experiments prove that the proposed model significantly improves the state-of-the-art with respect to handling heterogeneous IoT devices, diverse network conditions, and the dynamic nature of cross-network optimization. With exhaustive experimentation, the model demonstrates an amazing network throughput increase of 45% in various environments by beating the current resource allocation approaches such as Method by 30%, and those with a relatively advanced approach, such as Method, by 18%. A few of the major metrics for latency in 5G networks were reduced by about 45% in dense urban areas, while approximately 30-35% was realized in suburban and rural environments, proving that this model effectively reduces delays and enhances real-time communication. By comparison, the average latency in Method [3] was about 25-30 ms, while here, in this work, the latency was as low as 12.3 ms in the urban setting and 18.7 ms for the rural setting, hence guaranteed to be ultra-low latency in communication across diverse topologies of networks. In addition, packet loss is reduced by 68%, thus satisfying highly robust communication reliability in highly congested scenarios. Moreover, this work also validated the privacy-preserving capabilities of the model, demonstrating that the model achieved a 90-95% reduction in privacy risk, whereas the improvement with regard to centralized approaches, such as Method [3], was only about 55-60% of privacy risks reduced. Moreover, at the introduction of DATL, it became possible to reduce cross-domain adaptation time by 50%, thus making knowledge transfer seamless between urban and rural networks in as little as 22 minutes, compared to 40 minutes in traditional models. Considering the overall effect of MAPPO, TA-PFed, and DATL, it proves that the model is scalable, efficient, privacy-preserving, and reduces data transmission cost. It adapts fastly to new network environments.

Federated learning mechanisms validate the model fit for distributed and privacy-sensitive IoT networks by 40% to 45% in reducing data transmission cost sets.

Future Scopes

While the proposed model has obtained huge success, there are quite a few future directions of consideration regarding further improvement of performance and applicability. First, though the model deals with the dynamic nature of 5G networks effectively, it still needs some room for optimization in highly mobile environments, such as vehicular networks. The extended model will be further beneficial for including highly mobile IoT devices facing fast network variation for real-time decision-making in ultra-reliable low-latency communication. Currently, DATL is implemented for domain adaptation between an urban and a rural environment. In the future, more detailed domains could be considered: the level of network congestion and/or the frequency of IoT-traffic pattern. This would allow more fine-grained transfer learning models that could handle micro-level domain variations. Another very promising area is the integration of reinforcement learning with deep learning-based perception for better contextual understanding of network states to enhance optimization of resource allocation by the agent in highly volatile network environments. Finally, future work could improve the robustness of federated learning in intermittent connectivity conditions-a persistent problem in rural and less well-off areas. Application of asynchronous or communication-efficient federated learning might extend applicability to low-bandwidth or high-latency settings and reduce dependence on a stable high-bandwidth connection even further. A combination of these enhancements could further improve the performance of collaborative resource management performance in 5G networks. It could be used to lay the ground for developing intelligent, scalable, and adaptive resource management systems in next-generation wireless networks.

6. References

[1] M. Beshley, N. Kryvinska and H. Beshley, "Energy-Efficient QoE-Driven Radio Resource Management Method for 5G and Beyond Networks," in IEEE Access, vol. 10, pp. 131691-131710, 2022, doi: 10.1109/ACCESS.2022.3228758.
keywords: {5G mobile communication;Quality of experience;Energy efficiency;Resource management;Quality of service;Energy consumption;Radio access networks;Energy consumption;energy efficiency;heterogeneous networks (HetNet);quality of experience (QoE);radio resource management (RRM);radio access network (RAN);resource allocation;voronoi diagram},

[2] N. H. Mahmood, O. A. López, H. Alves and M. Latva-Aho, "A Predictive Interference Management Algorithm for URLLC in Beyond 5G Networks," in IEEE Communications Letters, vol. 25, no. 3, pp. 995-999, March 2021, doi: 10.1109/LCOMM.2020.3035111.
keywords: {Interference;Ultra reliable low latency communication;Signal to noise ratio;Transmitters;Reliability;Prediction algorithms;Resource management;Beyond 5G/6G networks;intelligent resource management;interference prediction;URLLC},

[3] N. K. M. Madi, M. M. Nasralla and Z. M. Hanapi, "Delay-Based Resource Allocation With Fairness Guarantee and Minimal Loss for eMBB in 5G Heterogeneous Networks," in IEEE Access, vol. 10, pp. 75619-75636, 2022, doi: 10.1109/ACCESS.2022.3192450.
keywords: {Quality of service;5G mobile communication;Resource management;Downlink;Delays;Long Term Evolution;Streaming media;Radio resource management;QoS awareness;downlink RBs allocation;delay-sensitive traffic;service fairness;HetNets;5G eMBB},

[4] X. Gao, J. Wang and M. Zhou, "The Research of Resource Allocation Method Based on GCN-LSTM in 5G Network," in IEEE Communications Letters, vol. 27, no. 3, pp. 926-930, March 2023, doi: 10.1109/LCOMM.2022.3224213.
keywords: {5G mobile communication;Device-to-device communication;Resource management;Logic gates;Feature extraction;Interference;Signal to noise ratio;5G;LSTM;GCN;resource allocation},
[5] N. Zarin and A. Agarwal, "Hybrid Radio Resource Management for Time-Varying 5G Heterogeneous Wireless Access Network," in IEEE Transactions on Cognitive Communications and Networking, vol. 7, no. 2, pp. 594-608, June 2021, doi: 10.1109/TCCN.2021.3063132.
keywords: {5G mobile communication;Resource management;Long Term Evolution;Throughput;Rats;Wireless networks;Optimization;Hybrid resource management;5G heterogeneous wireless access network;congestion control;Lyapunov optimization},
[6] K. Suresh Kumar, J. A. Alzubi, N. M. Sarhan, E. M. Awwad, V. Kandasamy and G. Ali, "A Secure and Efficient BlockChain and Distributed Ledger Technology-Based Optimal Resource Management in Digital Twin Beyond 5G Networks Using Hybrid Energy Valley and Levy Flight Distributer Optimization Algorithm," in IEEE Access, vol. 12, pp. 110331-110352, 2024, doi: 10.1109/ACCESS.2024.3435847.
keywords: {Resource management;Task analysis;Blockchains;Costs;Optimization;Distributed ledger;5G mobile communication;Security;Digital twins;Object detection;Virtualization;Secure and efficient blockchain;distributed ledger technology;optimal resource management;digital twin beyond 5G networks;hybrid energy valley with lévy flight distribution optimization},
[7] T. T. Thanh Le and S. Moh, "Comprehensive Survey of Radio Resource Allocation Schemes for 5G V2X Communications," in IEEE Access, vol. 9, pp. 123117-123133, 2021, doi: 10.1109/ACCESS.2021.3109894.
keywords: {Vehicle-to-everything;5G mobile communication;Quality of service;3GPP;Sensors;Resource management;Reliability;5G V2X communication;frequency resource;ITS;resource allocation;vehicular network},
[8] F. S. Samidi, N. A. M. Radzi, W. S. H. M. W. Ahmad, F. Abdullah, M. Z. Jamaludin and A. Ismail, "5G New Radio: Dynamic Time Division Duplex Radio Resource Management Approaches," in IEEE Access, vol. 9, pp. 113850-113865, 2021, doi: 10.1109/ACCESS.2021.3104277.
keywords: {5G mobile communication;Transmitting antennas;Software algorithms;Interference;Quality of service;Machine learning;Energy efficiency;5G;resource management;machine learning;wireless communication},
[9] A. J. Morgado, F. B. Saghezchi, S. Mumtaz, V. Frascolla, J. Rodriguez and I. Otung, "A Novel Machine Learning-Based Scheme for Spectrum Sharing in Virtualized 5G Networks," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 10, pp. 19691-19703, Oct. 2022, doi: 10.1109/TITS.2022.3173153.
keywords: {5G mobile communication;Resource management;Interference;Computer architecture;Clustering algorithms;Microprocessors;Licenses;5G;network management;machine learning;network function virtualization;radio spectrum management;resource allocation;software-defined networking},
[10] R. -H. Hwang, F. Marzuk, M. Sikora, P. Chołda and Y. -D. Lin, "Resource Management in LADNs Supporting 5G V2X Communications," in IEEE Access, vol. 11, pp. 63958-63971, 2023, doi: 10.1109/ACCESS.2023.3288699.
keywords: {Vehicle-to-everything;Resource management;5G mobile communication;Optimization;Interference;Signal to noise ratio;Quality of service;Vehicle-to-everything;5G;local access data network (LADN);optimization;resource management;vehicle-to-everything (V2X) communications},
[11] F. Debbabi, R. Jmal, L. C. Fourati and R. L. Aguiar, "An Overview of Interslice and Intraslice Resource Allocation in B5G Telecommunication Networks," in IEEE Transactions on Network and Service Management, vol. 19, no. 4, pp. 5120-5132, Dec. 2022, doi: 10.1109/TNSM.2022.3189925.
keywords: {5G mobile communication;Resource management;Network slicing;3GPP;Radio access networks;Quality of experience;Next generation networking;5G;B5G;6G;network slicing;resource allocation;admission control;optimization algorithms;QoS;QoE},
[12] S. S. Sefati et al., "A Comprehensive Survey on Resource Management in 6G Network Based on Internet of Things," in IEEE Access, vol. 12, pp. 113741-113784, 2024, doi: 10.1109/ACCESS.2024.3444313.
keywords: {6G mobile communication;Resource management;Internet of Things;5G mobile communication;Surveys;Quality of service;Routing protocols;6G network;Internet of Things;resource management;survey;quality of service (QoS)},

[13] M. Maule, J. S. Vardakas and C. Verikoukis, "A Novel 5G-NR Resources Partitioning Framework Through Real-Time User-Provider Traffic Demand Analysis," in IEEE Systems Journal, vol. 16, no. 4, pp. 5317-5328, Dec. 2022, doi: 10.1109/JSYST.2021.3115896.

keywords: {5G mobile communication;Computer architecture;Real-time systems;Dynamic scheduling;Protocols;Cloud computing;3GPP;5G;5G New-Radio (5G-NR);cloud radio access network (C-RAN);network slicing (NS);resources optimization;service-based architecture;testbed},

[14] Y. Kim and H. Lim, "Multi-Agent Reinforcement Learning-Based Resource Management for End-to-End Network Slicing," in IEEE Access, vol. 9, pp. 56178-56190, 2021, doi: 10.1109/ACCESS.2021.3072435.

keywords: {Resource management;Network slicing;5G mobile communication;Dynamic scheduling;Quality of service;Delays;Computer architecture;5G;network slicing;multi-access edge computing;network resource management;multi-agent reinforcement learning},

[15] Y. Kim and H. Lim, "Multi-Agent Reinforcement Learning-Based Resource Management for End-to-End Network Slicing," in IEEE Access, vol. 9, pp. 56178-56190, 2021, doi: 10.1109/ACCESS.2021.3072435.

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