6G Network and AI: Integration Enabling Intelligent Adaptive, and Beyond 5g Wireless Systems

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Abstract— Beyond-5G and 6G Wireless Systems are required to enable services and technologies with extremely high data rates, ultra-low latency, enormous numbers of connections, and significantly less energy than current systems.

Additionally, the broad array of operational environments associated with 6G will pose significant challenges for traditional fixed resource management policies. This paper outlines a Research Plan based upon a doctoral thesis outline that enables us to incorporate Artificial Intelligence (AI) and Machine Learning (ML) into Adaptive Resource Allocation and Network Orchestration. The Research Plan is designed to utilize AI/ML to manage Ultra Dense Heterogeneous Networks (UDHN) employing Terahertz (THz) Communication, Ultra-Massive Multiple Input Multiple Output (UM-MIMO), and Reconfigurable Intelligent Surfaces (RIS). Our Research Plan defines Resource Management as an Optimization Problem involving the simultaneous optimization of multiple objectives including Subcarrier Assignment and Transmission Power, while satisfying constraints related to Delay Limitation, Power Limitation, and Interference Limitation. To resolve this Non-Convex Optimization Problem and the time varying nature of Channel Conditions, we propose a Multi-Agent Deep Reinforcement Learning (MADRL) Architecture consisting of Custom Deep Q-Network (DQN) Modules and Proximal Policy Optimization (PPO) Modules, enabling Flexible Decision Making.

Additionally, we plan to utilize Explainable Artificial Intelligence (XAI) to explain the Logic behind our Resource Management Decisions. We also plan to evaluate the validity of our Methodology through Simulation Studies utilizing MATLAB for Physical Layer Modeling and Channel Modeling, Python based TensorFlow/PyTorch Platforms for AI Model Training, and NS-3 for Network Level Modeling. We also plan to Generate Artificial CSI under Mobile and Blocked Conditions and utilize these Artificial CSI Data Sets to Compare our Approach to Proportional Fair Scheduling, Waterfalling Power Allocation, and several other Deep Learning 5G Baselines. Since this outline describes the Experimental Design but does not report on any Actual Experimental Results, No Performance Metrics have been included in this paper. Instead, this paper outlines the Experimental Designs, Evaluation Metrics, Predicted Results, Limitations, and Criteria for Demonstrating the Feasibility of our Proposed Contributions.

Index Terms—6G, beyond 5G, Artificial Intelligence, Machine Learning, Multi-Agent Deep Reinforcement Learning, Federated, Learning, Explainable AI, Terahertz Communication, Resource Allocation, Interference Mitigation, RIS, UM-MIMO.

I. INTRODUCTION

As wireless communications have evolved from primarily voice-centric services, to those which are now heterogeneously designed to provide access for broadband, machine-to-machine communication, industrial automation and latency sensitive applications, it can be said that 5G has taken us into the age of enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC) and massive machine type communication (mMTC). This project's motivation and outline state that new emerging application areas including autonomous vehicle technology, holographic telepresence, the Internet of Everything (IoE) and Extended Reality (XR) require much higher performance than what current 5G technologies can deliver.

Consequently, 6G represents a natural progression in research, offering a more intelligent and heterogeneous communication platform, rather than merely a faster version of 5G.

6G will have many advanced physical layer and network technologies. The paper listed terahertz (THz) communications, ultra-massive multiple input

multiple output (UM-MIMO), reconfigurable intelligent surfaces (RIS), and visible light communications as some of the main physical layer technologies. Each of these technologies create additional challenges in managing resources.

For example, in order to respond to very quickly changing channel conditions, user densities, interference levels and application needs, the network must be able to adapt quickly.

As a result, using traditional mathematical optimization or heuristic based resource management techniques will be extremely challenging to use in real-time due to the fact that the system is both highly non-linear and rapidly changing.

Thus, artificial intelligence (AI) and machine learning (ML) are being considered as potential ways to transition towards an AI- native network architecture.

The AI integration identified in the synopsis can be viewed through three distince yet complementary lenses: AI for Newtork (AI4NET), Network for AI (NET4AI), and a Service (AIaasS).

Although this study will focus primarily on AI4NET by utilizing learning-based control to improve network performance; federated and edge-oriented learning are used to facilitate the distributed computing aspect of the network. The principal research question is how to develop and optimize a smart, AI-native architecture for resource allocation and interference reduction in ultra-dense heterogeneous Beyond-5G/6G networks. The synopsis highlights that there are specific areas for investigation which include dynamic spectrum and power allocation, communication-efficient federated learning using high-frequency links, and explainable network orchestration.

Thus, the study will integrate MADRL, FL, and XAI in a cohesive manner rather than independently.

II. BACKGROUND AND RELATED CONCEPTS

A. Beyond-5G and 6G Network Requirements

The summary defines 6G as a major change in how we will use technology due to new needs for speed and capacity (e.g., peak data rate over 1 terabit per second (TBPS), users experience speeds over 10 gigabits per second (GBPS), latency is less than one millisecond, and device densities are over 10 million devices per square kilometre). This means that these numbers represent target design parameters set forth in the summary rather than actual performance metrics of a working 6G system. To achieve the ambitious goals set out, an organized approach will need to take place in order to maximize various aspects of this technology such as radio wave transmission and propagation, how much space is available for use (spectrum), how much electricity is consumed (power), what amount of computing capability can be utilized (computational resource), and the way in which all of the different components work together within the larger system (network orchestration).

Therefore, the summary highlights that adaptive beamforming and channel tracking enabled through machine learning techniques will play an important role in enabling successful deployment of 6G systems.

B. AI for Wireless Resource Management

Machine learning (ML) has grown in popularity as it applies to wireless communications since many of the choices made regarding networks are based on large-scale and dynamically changing observations. Ohtsuki identified artificial intelligence/machine learning (AI/ML) as a significant part of future 6G wireless communication additionally, he reviewed methods of learning that apply to the physical layer [3]. Rekkas et al. reviewed supervised, unsupervised, and reinforcement learning techniques for systems beyond 5G/6G and outlined areas of future research for wireless intelligent systems [4]. Reinforcement learning is well suited to address the problem of allocating resources since it involves making a series of decisions over time.

A decision maker (agent) receives information from the network about its current status, takes an action (assigning resources or setting transmit power), receives some type of feedback (reward), and then receives new information about the network's current status. If there are multiple base stations or edge devices involved in interacting with one another, this decision-making process will naturally be expanded to include multiple agents.

C. THz Communication, UM-MIMO, and RIS

THz communication is a good choice for 6G since there are so many high frequency bands available; however, the same band also leads to significant sensitivity regarding molecular absorption, distance and physical obstructions. The two technology solutions described above, ultra-massive multiple-input/multiple-output (UM-

MIMO) systems and reconfigurable intelligent surfaces (RIS), each have distinct capabilities that enable them to enhance communication performance in different ways.

The combination of these factors makes up a flexible yet complex radio environment in which resource decisions are impacted by the propagation conditions. Rekkas et al. identify intelligent reflecting surfaces and high-frequency communications as important areas in ML-enabled beyond-5G/6G research [4].

D. Federated Learning for Distributed Intelligence

Federated Learning enables participants to collaboratively create a common machine learning model while ensuring that none of them need to share their individual raw training data. The classical formulation aggregates locally computed model updates and therefore has relevance in environments with distributed data, some of which may be private. McMahan et al., using an iterative model averaging technique, developed a communication-efficient method for distributed learning and considered communication costs to be the main limiting factor [7]. The most critical aspect of the proposed 6G system will be how to provide reliable communication channels for the exchange of models across wireless networksThese pathways might be required to function amidst regular connectivity interruptions caused by elements like THz signal obstruction and movement.

E. Explainable AI for Network Decisions

Deep Learning (DL) and Reinforcement Learning (RL) have shown an ability to make good decisions; however, they cannot provide a logical explanation for how these decisions were made.

In addition, when there is a critical need to understand what data was used by the neural network to arrive at its final decision, management will be required to determine exactly which pieces of data contributed to the decision. SHAP provides a general framework for assigning feature-importance values to individual model predictions and is therefore a suitable XAI mechanism for investigating the relationship between network state and resource-management decisions [8].

III. LITERATURE REVIEW

The studies cited in the synopsis are the basis of why there is a need for AI-native 6G and what problems exist with implementing it. The following review will focus on the studies from the synopsis that directly relate to the proposed Resource Management Problem, as shown in Table I.

Table I
Summary Of Reviewed Literature

Study	Focus	Contribution	Limitation
Chataut et al. [1]	6G technologies, applications, and AI	Reviews 6G requirements and the role of AI/ML.	Broad survey; does not address the joint MADRL–FL–XAI problem.
Maduranga et al. [2]	AI-enabled 6G IoT	Examines AI/6G integration for IoT; discusses scalability, security, and ethics.	No specific adaptive allocation framework.
Tagami et al. (as cited in synopsis)	AI for Network / Network for AI	Frames the bidirectional AI–network relationship and autonomous operation.	Conceptual; lacks measurable allocation and interference mitigation.
Rekkas et al. [4]	ML in beyond-5G/6G	Reviews ML methods and technologies including IRS/RIS and high-frequency communications.	Review-level; adaptive multi-agent allocation remains open.
Ohtsuki [3]	ML in 6G wireless	Surveys AI/ML techniques with emphasis on physical-layer use.	Does not implement the integrated MADRL, FL, and XAI framework.

The verified publication records also clarify two bibliographic points in the synopsis. Chataut et al. appeared as a peer-reviewed Sensors article in 2024 after an earlier 2023 preprint, while Ohtsuki's article appeared in IEICE Transactions on Communications, vol. E106-B, no. 2, pp. 75–83 [1], [3].

IV. RESEARCH GAP

Synopsis points out four gaps that in conjunction make up the contributions of this study. Many high performing deep-learning methods are difficult to explain, which results in a trust/accountability issue for autonomous network control. The high computational costs associated with using complex models will negate any physical layer energy savings obtained by performing inference/training at the network edge. When using federated learning over unreliable THz links, packet loss/slow convergence could arise due to competition between large model updates and unreliable wireless connectivity.

Finally, single agent reinforcement learning is unable to properly model the interference caused by coupled interference sources in ultra-dense dynamically changing cell-free environments. These gaps are all interrelated. An allocation method that provides accurate results but is computationally intensive may not be suitable for use at the network edge; a distributed method that protects privacy but needs large/frequent updates may not be feasible over THz links; and a high performing autonomous controller that lacks interpretability may be difficult to rely upon in critical application settings.

Therefore, this research will use a single evaluation framework to investigate resource allocation, communication-efficient distributed learning, and explainability.

V. PROBLEM FORMULATION

The network can be viewed as a directed graph, with vertices representing the different components of the network (massive MIMO Base Stations, Reconfigurable Intelligent Surfaces, and End-User Devices), and edges indicating the wireless communication channels between them. The network operates on a set of orthogonal sub-carriers. The main decision parameters are the allocation of sub-carriers and the transmission power. The objective function is to maximize the sum of spectral efficiency and energy efficiency, subject to satisfying all three constraints: latency, power, and interference.

$U = \alpha \cdot SE(x, p) + \beta \cdot EE(x, p)$

where α and β represent the relative importance of spectral and energy efficiency, x denotes subcarrier-allocation decisions, and p denotes transmit-power decisions. The optimization is subject to

$L_{ij}(x, p) \leq L_{max}$

$\Sigma_k \, p_{ijk} \leq P_{max,i}$

$I_j(x, p) \leq I_{threshold}$

The parameters are summarized in Table II.

Table II
Parameters of the Optimization Problem

Parameter	Type	Interpretation
x_{ijk}	Binary decision variable	Allocation of subcarrier k to link (i, j)
p_{ijk}	Continuous decision variable	Transmit power on link (i, j), subcarrier k
L_{max}	Latency constraint	Bounds end-to-end delay for latency-sensitive services
$P_{max,i}$	Power constraint	Limits total transmit power at node i
$I_{threshold}$	Interference constraint	Limits interference and supports reliable decoding

The decision problem is a Markov Decision Process (MDP) because the optimization is highly non-convex and it depends on channel state information that changes very rapidly; thus, the synopsis proposes adaptive ML methods which can be used to achieve near-optimal solutions in real-time.

VI. RESEARCH OBJECTIVES

The research pursues the following objectives:

1) Develop a MADRL-based system for adapting to changes in spectrum and power usage within ultra-dense 6G networks dynamically and in real-time.
2) Develop an energy-efficient Federated Learning architecture to minimize communication overhead through high-frequency THz links.
3) Integrate Explainable AI (XAI) models into the resource-management system to provide a more transparent and accountable approach to network orchestration.
4) Benchmark the new AI-integrated solutions against both current and emerging 5G/Beyond 5G standards in a simulated environment with high mobility and high density.

These objectives are reproduced in substance from the synopsis and serve as the organizing principles for the proposed system, implementation plan, and evaluation protocol.

VII. PROPOSED METHODOLOGY

Proposed Methodology has four phases that were outlined in the synopsis: Mathematically Model the Environment and Design an Environment; Develop Algorithms; Simulate and Generate Data; Benchmark and Evaluate. The workflow has been illustrated as Fig. 1. This workflow was developed with a view to support learning using a simulated network state, distributed training of models, explainable analysis of results, and benchmarking of performance.

Fig. 1. Proposed research workflow derived from the dissertation synopsis.

A. Phase 1: Mathematical Modeling and Environment Design

The first stage defines the environment of the simulated 6G network. The physical layer environment will incorporate characteristics of THz channels, UM-MIMO antenna arrays, and RIS assisted propagation. The state representation will include the following data that each learning agent requires to make resource decisions: channel-state information, traffic/load conditions, latency indicator, power availability, and interference observations. The action representation will include subcarrier allocation and power control; however, whether these are represented by a discrete set of values or as continuous parameters depends upon how they are implemented. The reward function will optimize latency, throughput-related spectral efficiency, and energy efficiency by penalizing constraint violations. A general form that can be used for implementation is

$$R_t = w_1 SE_t + w_2 EE_t - w_3 L_t - w_4 I_t - w_5 P_{viol,\,t}$$

where the weights w1-w5 are hyperparameters to be determined through experimentation. Equation (5) implements the expansion of the synopsis's requirement for the reward balance latency, throughput, and energy efficiency; it does not mean that those weight selections are pre-made. B Phase 2: Development of the MADRL Algorithm.

B. Phase 2: MADRL Algorithm Development

In addition to using a DQN, we have also developed an algorithm that incorporates elements from both DQN and PPO to address the mixed decision-making processes of controlling continuous power levels while allocating discrete subcarriers. The first part of this algorithm uses a DQN because the number of possible actions in this scenario is discrete and finite; therefore, we can employ a neural network to learn the values associated with performing every possible action. DQN was initially developed in [5] where it was demonstrated that a DQN can be trained using reinforcement learning methods to develop policies based upon large dimensional input vectors. PPO is another type of algorithm that falls under the category of policy-gradient methods. PPO employs a clipped surrogate objective function that provides constraints on how much the policy can change at any given iteration, thereby providing more robust learning for systems with continuous control [6]. A multiple-agent system may be created by assigning one agent to every entity within the network that has control over its own resources or to groups of cells that logically belong together (Figure 2). The agents will receive information about their local environment and decide what action to take, while the environment will provide feedback to them in terms of a reward signal as well as a description of what the next state of the entire network will be. Evaluations of the system

should include both overall performance measures as well as performance metrics for each individual agent. This is because a high overall performance measure may not accurately represent the quality of resource allocations across all agents.

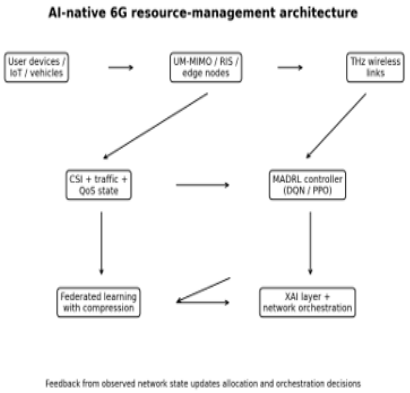

Fig. 2. AI-native 6G resource-management architecture.

C. Phase 2: Federated Learning and Communication Efficiency

The advantage of federated learning is that it allows the model to be trained on the distributed devices (referred to as edge devices) instead of collecting all the raw data from those devices and sending them to a central server for training. The description above provided an overview of how we intend to implement this type of system, which includes using model compression techniques such as quantizing gradients to help minimize the amount of data transferred over the network.

In order to properly evaluate our solution, we will establish an experimental methodology for recording parameters related to model updates (i.e., update size), the number of times we communicate with the edge devices (i.e., communication rounds), failures in transmitting data due to packet loss, the rate at which our model converges, and the accuracy of the final model. We will evaluate our proposed solution using two different types of THz link conditions: one that is relatively stable and another that is extremely volatile.

D. Phase 2: Explainable AI Integration

The XAI layer translates learning decisions into measurable network states. For a specific allocation decision, the analysis should identify which input parameters (e.g. channel quality, interference, traffic load, latency status and/or available power) had the greatest impact on the decision. The use of SHAP values would be an appropriate method since these values can provide information about how each parameter affects the prediction of a single instance [8]. Explanation is not intended to replace Performance Evaluation; rather it is considered to be a second dimension of validation.

Therefore, the system should both perform adequately and also provide sufficient evidence that its actions relate to physical network conditions.

E. Phase 3: Simulation and Synthetic CSI Generation

Because 6G hardware has been in the initial stages of research, it seems that there may be a simulation-based approach developed. A physical layer and channel representation would be made in MATLAB, while an AI model could be created with either PyTorch or TensorFlow (both of which are Python based frameworks). Also, NS-3 would be used to execute network-layer packet-level simulations. The artificial CSI data would represent the molecular absorption, obstacles and movement associated with THz signaling. The simulation dataset created from this data should be categorized according to the specific scenario that they relate to; however, they cannot remain one large, unorganized mess. Categorization should include details such as channel environment, traffic demand, obstacle state, level of movement and density of users. Because 6G hardware has been in the initial stages of research, it seems that there may be a simulation-based approach developed. A physical layer and channel representation would be made in MATLAB, while an AI model could be created with either PyTorch or TensorFlow (both of which are Python based frameworks). Also, NS-3 would be used to execute network-layer packet-level simulations. The artificial CSI data would represent the molecular absorption, obstacles and movement associated with THz signaling. The simulation dataset created from this data should be categorized according to the specific scenario that they relate to; however, they cannot remain one large, unorganized mess. Categorization should include details such as channel environment, traffic demand, obstacle state, level of movement and density of users. In order to assess how well the system generalizes to new channel realization

conditions (i.e. not just memorizing), training, validation and testing scenarios need to be separated.

F. Phase 4: Benchmarking and Evaluation

The proposed simulation evaluates the proposed methods based on device density (106 devices per square kilometer) and speed (1000 kilometers per hour) for use in aeronautical and/or vehicular applications The simulation objectives of this project, as stated in the proposal document, are distinct from those measured by the simulation itself. The performance of the methods proposed will be evaluated against proportional-fair scheduling algorithms; water-filling power allocation methods; and current 5G deep-learning baseline models. A diagram illustrating the integrated control loop used in this study is shown in Figure 3.

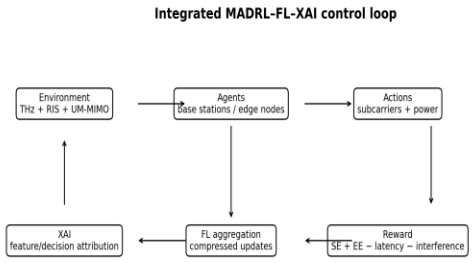

Fig. 3. Integrated MADRL–FL–XAI control loop proposed for the study.

VIII. DATASET AND DATA GENERATION

This synopsis is not defining the sample size for a publicly available (or otherwise) dataset. Rather, the synopsis is describing the generation of synthetic CSI data via a high-level system simulator.

Therefore, the authors did not define a specific sample size for their data. The authors will document how they created their data so others can reproduce it. The components of the data are listed in Table III.

Table III
Components of the Synthetic Dataset

Data component	Generation factors	Role
Channel state information	THz propagation, path loss, absorption, blockage	Learning state and channel-aware allocation
Network topology	Nodes, links, UM-MIMO/RIS configuration	Agent and environment definition
Traffic/load	User demand and offered load	QoS-aware resource allocation
Mobility	User speed and changing positions	High-mobility robustness
Interference	Inter-cell/inter-agent interference measures	Constraint and reward calculation
Power	Available and allocated transmit power	Energy-efficiency optimization
QoS indicators	Latency and reliability-related state variables	Constraint satisfaction and evaluation

IX. DATA PREPROCESSING AND EXPERIMENTAL PROTOCOL

Before beginning instruction, it is essential to check modelled data for missing or incorrect information resulting from failed simulations. I would recommend scaling numerical features with statistics based on the training part of the dataset. Additionally, when using categorical variables and scenario labels in either the training or evaluation phase, the same method of encoding should be used. If the learning architecture necessitates preserving temporal order, then temporal observations should retain this ordering. A better method for dividing the data than simply splitting the data randomly row-wise would be a scenario-based split. A scenario-based split would allow for the division of the training data in such a way that there will be a greater likelihood of preserving the correlation between adjacent CSI samples.

Additionally, the final test set should consist of channels and mobility conditions that were not utilized in updating model parameters.

Finally, hyperparameter tuning should utilize the training/validation partition; however, the test set should only be utilized for final benchmarking.

X. IMPLEMENTATION FRAMEWORK

The planned software stack, which follows the synopsis, is given in Table IV.

Table IV
Planned Implementation Tools

Component	Planned tool	Primary role
Physical/channel modeling	MATLAB	THz channel characteristics, UM-MIMO, RIS-assisted propagation
AI model training	Python + TensorFlow /PyTorch	DQN/PPO and multi-agent learning
Network simulation	NS-3	Packet-level network behavior and communication effects
Distributed learning	Python-based FL implementation	Local training, aggregation, compression
Explainability	XAI library / SHAP-compatible analysis	Feature attribution and decision analysis

The exact versions of libraries used as well as the specific details about the hardware configuration, random seed values, number of training iterations (episodes), learning rate, batch size, dimension of networks, and compression ratio will need to be documented at the time each experimental run is performed. These are implementation specific details and therefore they were not defined in the abstract and do not appear to have been made up for the purpose of writing this article.

XI. PERFORMANCE EVALUATION

You will assess the five research objectives in addition to the reported single value of accuracy for each objective. The main performance metrics are spectral efficiency, energy efficiency, latency, interference behavior, resource-allocation stability, federated-learning communication overhead, convergence behavior and explainability evidence (Table V and Figure 4).

Table V
Evaluation Metrics

Metric	Purpose	Evaluation use
Spectral efficiency (SE)	Data throughput per unit bandwidth	Compare proposed MADRL with baseline scheduling/power methods
Energy efficiency (EE)	Useful throughput relative to energy consumption	Evaluate trade-off under different loads and densities
Latency	Delay against the stated latency constraint	Check constraint satisfaction, especially under high load
Interference	Interference experienced by links or agents	Assess whether multi-agent coordination reduces harmful interference
FL communication overhead	Update size and communication rounds	Compare compressed and uncompressed learning protocols
Convergence	Learning progress toward a stable policy/model	Compare learning stability across scenarios
XAI consistency	Whether explanations match meaningful state variables	Inspect feature attributions and decision traces

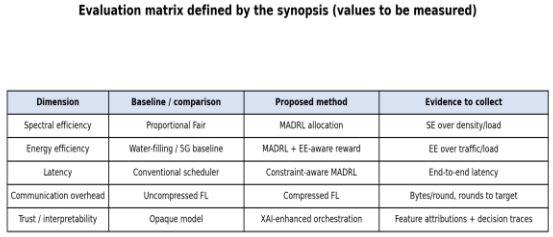

Fig. 4. Evaluation matrix defined by the proposed study; numerical values are intentionally omitted until experiments are completed.

XII. COMPARATIVE ANALYSIS

The main comparison should not illustrate how AI will consistently do better than traditional optimization. Each of the baseline models need to be assessed with

identical channel realization, network topology, traffic conditions and resource constraints.

Proportional fair scheduling provides an optimization-based scheduling baseline, Water-Filling provides an optimization-based power-allocation baseline and a 5G Deep Learning baseline provides a learning-based reference point for comparison. By controlling the environment in which all three methods are tested; we can attribute any observed improvements in performance to our proposed adaptive architecture (Table VI)

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Table VI
Comparison of Methods to Be Benchmarked

Method	Function	Type	Purpose	Result status
Proportional fair	Scheduling	Conventional	Benchmark fairness/throughput	To be measured
Water-filling	Power allocation	Optimization	Benchmark power allocation	To be measured
5G deep-learning baseline	Learning-based optimization	AI/ML	Compare with existing learning approach	To be measured
Proposed MADRL	Joint dynamic allocation	Multi-agent RL	Adaptive spectrum/power decisions	To be measured
Proposed MADRL + FL + XAI	Distributed, explainable orchestration	Integrated AI	Full proposed framework	To be measured

XIII. RESULTS AND DISCUSSION

A. Status of Experimental Results

The submitted abstract has not provided any numerical data from an actual experiment. The abstract outlines a plan for conducting a simulation/benchmark and identifies what the expected outcome will be (i.e. SE, EE, latency, accuracy, training time, communication overhead, convergence).

Therefore, I chose to omit inventing my own numerical results in this document. Rather than being based on experimentally derived numerical results, the research contribution of this document remains a proposed framework that needs validation.

B. Expected Interpretation of the Evaluation

If the proposed MADRL controller develops the ability to develop optimal policies, then it can be anticipated that the proposed MADRL controller will lead to more efficient resource allocations based upon dynamic changes in channel and traffic conditions than what could be achieved using either fixed or conventional baseline controllers.

Additionally, it is anticipated that the proposed MADRL controller will provide near-optimal dynamic allocations and improve the performance (both SE and EE) of current 5G baseline models. This is an expectation of the proposed MADRL controller's capabilities; it is not a direct observation of the proposed MADRL controller's capabilities. With regard to federated learning, the primary goal of this research is to create a more communication-efficient distributed learning process operating within a volatile THz environment. The primary data points relevant to this research are the convergence characteristics of the distributed learning process, the size of each update, the percentage of packets lost during each update, and the number of rounds required to complete each distributed learning process. Similar to the previous section, the primary objective of this research is to predict what will happen once the proposed federated learning technique is implemented in practice. The final area of research concerns explainable artificial intelligence (XAI). The main objective of this research is to show that decision-making processes produced by deep learning algorithms can be related to specific network states.

Therefore, a meaningful analysis of XAI would involve providing representative explanations of decisions made at various channel, interference,

mobility, and traffic condition points, as opposed to simply generating a single global feature importance graph.

XIV. REPRODUCIBILITY AND REPORTING REQUIREMENTS

This project will have the potential to be a credible empirical work and will provide detailed information about how the simulation environment was set up, what assumptions were made about each channel used in the simulation, how each topology was developed using the methods outlined in this document, and which random seed was used to generate each result. The final product will also include all hyperparameters that were selected for each model tested in this project, the length of time that each model was trained for, all baseline parameters used in this experiment, and all evaluation scripts developed to assess each model. When applicable, results from multiple independent simulations may be displayed with associated uncertainty measures (e.g., confidence intervals, standard deviations).

Additionally, improvements toward achieving learning objectives can be separated from those improvements attributable to increased physical network efficiency.

Furthermore, it is essential that the proposed model and the comparative models being evaluated are utilizing comparable amounts of data.

For example, if a MADRL model has access to significantly more fine-grained state data than its comparative baseline, then a simple comparison may lead to inaccurate conclusions. Similarly, an objective evaluation of uncompressed vs compressed Federated Learning cannot occur if their respective local training allocations vary or if they are allowed to participate in different periods.

XV. LIMITATIONS

- The simulation-based research is necessitated by the fact that there are no commercially available 6G/THz devices, nor are there standard deployment scenarios for the assessment being performed.
- The synthetic channel state information (CSI) used in this work is based upon the simulator models and assumptions used to create them.
- The reward function is dependent on the weights that are chosen for the various objectives (e.g., spectral efficiency, energy efficiency, etc.) which may lead to varying trade-offs between these objectives.
- The computational requirements of MADRL are significant and increasing the number of agents could cause training instability or additional coordination overhead.
- Federated learning performance is affected by non-IID data, the number of clients participating in the process, failure of links connecting the client to the server, and the type of update compression used; therefore, they need to be managed and recorded.
- The use of XAI (explainable artificial intelligence) explanations may help to make policies more interpretable, but these explanations cannot prove that a policy has been learned in a way that establishes causal correctness.
- The abstract does not identify either a publicly available dataset or any previously completed experimental studies; therefore, empirical claims still need to be verified.

XVI. FUTURE SCOPE

Further work in this area could involve the development of a hardware-in-the-loop validation environment based upon our proposed simulation method; more realistic mobility and/or blockage models; larger scale deployments involving multiple agents; and ultimately, cross-layer optimization techniques. Other areas of further research may include adaptive model compression, individualized or hierarchical federated learning and more resilient mechanisms against intermittingly available THz links. The XAI component can also be evolved beyond just being used to provide post-hoc explanations for agent actions and policies, into an interpretable policy design framework where interpretability requirements are incorporated into the learning process.

In addition, there may be opportunities to compare our proposed framework with other multi-agent algorithms and more recently developed distributed optimization techniques, provided they are evaluated using similar experimental setups as we have used. These additional studies should remain subservient to

the central issue of intelligent adaptive resource allocation and interference reduction.

XVII. CONCLUSION

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his article takes the dissertation abstract to develop a structured framework for research on how to integrate AI into future beyond 5G/6G wireless networks. The focus of the study is a specific systems problem: how to allocate resources dynamically and reduce interference in ultra-dense heterogeneous networks that have very strict QoS requirements and whose channel conditions change rapidly. The proposed solution involves MADRL to make decisions about adapting spectrum and power; communication-efficient FL to implement distributed intelligence through wireless links that are constrained in capacity; and XAI to allow for transparency when orchestrating the network. The methodology is designed to be purely simulation-based using MATLAB, Python-based AI platforms, and NS-3 to create a repeatable environment for testing. The mathematical formulation defines a single objective (spectral/energy efficiency), yet also maintains constraints related to latency, power, and interference. The evaluation plan will compare the proposed method with proportional-fair scheduling, water-filling, and relevant 5G learning baseline methods across various levels of density and mobility. The primary academic contribution of this work thus far is a well-structured, testable framework for research, rather than a quantifiable measurement of performance. After the planned simulations have been completed, the obtained quantitative data will be placed into the previously defined evaluation tab
les and figures while continuing to maintain the distinction between expected results and experimentally proven ones.

REFERENCES

[1] Chataut, R., M. Nankya, and R. Akl, "6G networks and the AI revolution—Exploring technologies, applications, and emerging challenges," Sensors, vol. 24, no. 6, Art. no. 1888, 2024, doi: 10.3390/s24061888.

[2] Maduranga, M. W. P., V. Tilwari, R. M. M. R. Rathnayake, and C. Sandamini, "AI-enabled 6G Internet of Things: Opportunities, key technologies, challenges, and future directions," Telecom, vol. 5, no. 3, pp. 804–822, 2024, doi: 10.3390/telecom5030041.

[3] Ohtsuki, T., "Machine learning in 6G wireless communications," IEICE Transactions on Communications, vol. E106-B, no. 2, pp. 75–83, 2023, doi: 10.1587/transcom.2022CEI0002.

[4] Rekkas, V. P., S. Sotiroudis, P. Sarigiannidis, S. Wan, G. K. Karagiannidis, and S. K. Goudos, "Machine learning in beyond 5G/6G networks—State-of-the-art and future trends," Electronics, vol. 10, no. 22, Art. no. 2786, 2021.

[5] Mnih, V., et al., "Human-level control through deep reinforcement learning," Nature, vol. 518, pp. 529–533, 2015, doi: 10.1038/nature14236.

[6] Schulman, J., F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," arXiv preprint arXiv:1707.06347, 2017.

[7] McMahan, H. B., E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS), PMLR, vol. 54, pp. 1273–1282, 2017.

[8] Lundberg, S. M., and S.-I. Lee, "A unified approach to interpreting model predictions," in Advances in Neural Information Processing Systems (NeurIPS), vol. 30, pp. 4765–4774, 2017.