

AI-Optimized Beamforming and Resource Management in Terahertz 6G Networks with IoT Integration Spectrum Efficiency

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Abstract

This study focuses on the role of artificial intelligence in optimizing joint beamforming and resource management to improve spectrum efficiency for massive Internet of Things (IoT) in Terahertz (THz) 6G networks. The research aims to find intelligent solutions to help accomplish ultra-high data rates and massive connectivity in 6G network ecosystems where there exists the problem of THz high path loss due to molecular absorption and blockage. The emphasis of the study was on developing and optimizing a joint beamforming and resource allocation framework using deep reinforcement learning (DRL) architectures, subsequently using performance improvement on networks metrics as a main consideration. Based on the positivist theoretical framework, the research applied an experimental simulation-based research method in an integrated environment of MATLAB-ns-3-PyTorch and physics-based TeraMIMO channel model. The generation of synthetic data (i.e. channel realization) was used to create 500,000 samples using stratified equal sampling of five scenarios (i.e., varying density and mobility levels of IoT) where each scenario was represented by 100,000 samples. Monte-Carlo analysis and statistical tests confirmed improvements in Latency, System Reliability and Energy Efficiency (EE) by 738%, 3.1 ms, and 97.9%, respectively, as compared to the traditional methods. The results also confirmed an increase in the Spectral Efficiency (SE) ranging from 500–611%.

Keywords: Terahertz 6G, AI Beamforming, Resource Management, Spectrum Efficiency, Deep Reinforcement Learning, Iot Integration, Joint Optimization, Massive Connectivity

Introduction

The arrival of sixth-generation (6G) networks signifies an unprecedented revolution in new-age communication technologies. Edward Husain (2026), Balaji et al. (2025), and Zhou (2026) suggest that the foundations of such advancements include terabits per second rates of data transfer, ultralow latency, and near-zero delay new-age communications (such as interactive holograms and autonomous multi-robot systems). The distinct bands of terahertz (THz) (between 0.1 and 10 THz) will be at the epicenter of 6G communications, exhibiting ultrahigh frequency and wider bandwidth than the frequencies of millimeter and sub-6 GHz waves. Despite all these promises, there will be significant hurdles to overcome in the 6G THz wave communication systems (such as high path loss, molecular absorption, and increased sensitivity to the THz channel). Such systems demand the advanced management of beams, as well as feature-optimizing type intelligent systems. The mesh of IoT systems and intelligent management of beams relies on the optimal dynamic distribution and management of the systems of advanced and heterogeneous units. The concern of beam scattering in the THz range is of particular significance in this case. It is in this context that

the new decision-making and management technologies of the Deep Reinforcement Learning (DRL) and Neural Networks games in the field of the THz-6G communication systems will find their application, and the supply of devices will expand as highly adaptive beam management systems will be developed.

Resource management in THz 6G networks entails the optimization of power allocation, spectrum sharing, and computing resources, and is made dimly more complex in the face of massive IoT deployments (Rajeswari, 2025). Advanced AI methods, including federated learning and artificial neural networks, offer intelligent, decentralised decision-making that occurs in real-time and is flexible to the systems' heterogeneity and traffic spiking. In comparison to traditional systems that depend on static allocation, these methods are more efficient and maximally allocate resources in a proactive manner. They enhance the spectral efficiency and energy efficiency of a network (Alhashimi et al., 2025). In the case of IoT, where the network of devices encompasses low-powered sensors and high powered terminals, AI stands to ensure optimal distribution of network resources and also of network function slices (Kamal, 2026).

The integration of both AI and THz communications is referred to as the 'symbiotic' phase, where AI in conjunction with THz tackles specific limitations of each of the technologies, and THz supports AI-centered applications by dynamically integrating sensing and communications (ISAC). Studies indicate that the use of machine learning in assignments including but not limited to the management of very large MIMO utilizes THz for ultra-massive MIMO systems, and is the most effective option (Terahertz, 2026). As a result, the integration of AI and THz communications is capable of facilitating support of billions of flexible IoT devices with ultra-low latency, as beamforming and resource scheduling are dynamically and optimally performed to ensure spectral efficiency is maintained despite changing circumstances (Tok, 2026; Das, 2025).

In the development of THz 6G with IoT, the metric that matters is what you can practically do with the available bandwidth. 6G brings AI on board, and the potential ergonomic gains of AI Heterogenous Networking Systems are evident (Hussain, 2026). Machine learning models can create intelligent flows that can optimize modulation, optimize coding, and optimize beam forming. Reconfigurable intelligent surfaces (RIS) can have feedback intelligent surfaces that can reflect signals that can go around obstacles (Balaji et al., 2025; Sefati, 2024). Optimizations of IoT dense scenarios can achieve significant reductions per bit and sustain high density deployments for the energy needed. That is the vision of a 6G ecosystem.

It is a fact that there is an AI-optimized solution and the computing cost increases dramatically in difficult scenarios for THz. The computing cost in edge devices is the concern. Those that are not included have the risk of increased complexity in IoT devices with limited resources (Zhou, 2026). The objective ideally is to achieve intelligent spectrum-efficient 6G networks. Intelligent systems that rely on AI, cater to beam forming and resource optimization, and make use of THz bands within IoT show a paradigm shift toward the optimization of autonomous and more efficient 6G systems. Since these networks make use of DRL framework for the optimization of resources and for the first time, the adoption of federated learning. Of course, AI-optimized and beam formed networks can change the world for the better (Alhashimi et al., 2025; Rajeswari, 2025). Research in the intersection of AI, materials science and wireless engineering is anticipated to move quickly in order to improve the prototypes that are a great improvement over the simulation (Faraj et al., 2025).

This introduction highlights the importance of AI in developing THz technology, improving resource management in IoT-focused 6G, and establishing the groundwork for in-depth studies of algorithms and architectures alongside performance assessments. The continued growth of wireless technology will also concentrate on generative AI models and digital twins for predictive optimization, signalling further advancements in spectrum efficiency (Terahertz, 2026; Tok, 2026; Das, 2025).

Research Questions

1. In what ways do AI-based beamforming techniques improve spectrum efficiency in Terahertz 6G technologies integrated with IoT?
2. What strategies based on AI resource management can optimally address power distribution and interference problems in a THz integrated 6G IoT framework?
3. Explain the impact of THz 6G beamforming and resource optimization on the AI-enabled extension of a resource management framework in massive IoT THz-G networks.

Research Objectives

1. Identify and develop AI beamforming solutions to address issues of spectrum efficiency in THz 6G IoT models.
2. Develop advanced 6G Terahertz solutions to provide intelligent resource management and improve required frameworks for interference rationalization and adaptive power distribution.
3. Evaluate the impact of AI-enabled beamforming and advanced resource management on major performance parameters in THz 6G massive IoT frameworks, focusing on system throughput, latency, and energy efficiency.

Significance of the Study

The importance of this study is clear for Terahertz 6G networks with IoT and how they are likely to enable ultra-high data rates and massive amounts of device connectivity to support new applications including holographic communication, autonomous systems, and smart cities. The research uses AI-optimized techniques to address the high path loss and interference and the issue of scarce resources available to be utilized in the THz bands, contributing to increased spectrum efficiency, energy savings, and improved reliability of the networks, thus facilitating more sustainable and scalable 6G deployments.

Literature Review

Among the myriad of technologies comprising six-generation (6G) mobile networking, the prospect of terahertz (THz) wireless communication is noteworthy, owing to its potential to enable the ultra-wide, ultra-efficient, terabit-per-second data rate transmission required to optimize the operation of the Internet of Things (IoT) (Hussain, 2026; Balaji et al., 2025). One of the earliest studies found rapid propagation failures in the THz frequency domain, such as substantial molecular absorption losses and being hypersensitive to the environment. Hence, design solutions in the THz wireless frequency domain suggest the huge demand and need for ultra-massive MIMO antennas and intelligent surfaces. Deployments of ultra-thin intelligent surfaces and ultra-massive antenna arrays promise to address unsolved complexities of THz spectral limitations in the dense IoT deployments (Shome, 2025).

THz regions of wireless communication have highly dynamic beam management issues. Popular technical solutions for adaptive smart antenna systems often exhibit slow adaptability to user mobility, channel fluctuations, and ultimately result in outages. Therefore, in the dynamically changing environments of the IoT radio communication nodes, narrow band energy targeting and reducing adverse interference to other communicating devices could be accomplished using predictive beam formation based on dynamic user mobility data, and channel state information. These approaches have been applied to advanced deep machine learning (DMG) incorporated instances of THz wireless communications, namely Deep Reinforcement Learning (DRL) in THz communications (Tok, 2026; Terahertz, 2026).

Resource management in THz 6G networks include numerous factors such as power allocation, sharing, interference control, and analyzing the diversity of IoT traffic. Traditional optimization techniques cannot handle the real-time scenarios, due to the computational complexities of these problems. AI methods, particularly federated learning and graph neural networks, enable distributed, real-time, and adversarial-

resource decision-making, while ensuring the best use of physical and spectral resources (Alhashimi et al., 2025). These frameworks are exceptional at resource management for low-powered IoT sensors and high data-rate applications at the same time.

The new design capability of RIS (Reconfigurable Intelligent Surfaces) + AI synergy, combined with THz, add enormous flexibility to the task of THz cell (base stations) in the IoT networks. RIS elements not only enable passive beam-forming, which mitigate the system blockages, to cover anisotropic area. Combined beam-forming, either active beam-forming at base stations, with soft actor-critic or DRL agents, plus passive RIS beam-forming, improve system performance to massive IoT networks (Kumar, 2025; Balaji et al., 2025). Studies prove that this kind of hybrid design of beam-forming and passive RIS, and spectrum constraint, yield a high disparity in system performance (Hussain, 2026).

Federated learning resolves the security and privacy issues pertaining to AI-optimized THz beamforming. Distributed training across edge devices not only preserves data locality, but also collaborative improvement of beam prediction. This technology secures the spectral performance coupled with URLLC in IoT applications (Rahmati, 2025; Toprak, 2025; Tok, 2026). Studies of recent dynamic THz channels show an improvement in performance and resilience. There are better results when using integrated AI frameworks for beamforming and resource management. Many systems are optimized using Deep Reinforcement Learning (DRL) based frameworks. These systems optimize power and subchannel and beam direction and achieve better spectral efficiency and lower latency in IoT systems. These systems are better at adapting to bursts of traffic and fluctuations in the environment compared to decoupled models. Integration of Integrated Sensing and Communication (ISAC) and multiple functionality Terahertz (THz) communication systems offers even more benefits for dual functionality systems (Ogenyi, 2025). Computational overhead for AI frameworks in Terahertz 6G beamforming and resource management poses some challenges, as do explainability and real-world AI models. Techniques from explainable AI (XAI) are using resource allocation and beam management decisions to improve the explainability and trust of the systems in question. Energy-aware designs and hybrid model-driven and data-driven systems balance performance and sustainability for constrained IoT devices. These systems have been documented (Tok, 2026; Alhashimi et al., 2025) and standardized to bridge the gap between simulation and prototypes and are postulated to execute AI optimization.

The documented gain of using AI optimization is well noted in modern literature. There is an indirect benefit of the efficiency gain in the systems when utilizing reinforcement learning and predictive analytic to dynamically change the systems modulation and coding. These systems change the beam patterns and achieve improvements between 2 and 3 folds. These systems are further enhanced using Reconfigurable Intelligent Surfaces (RIS) and AI solutions (Shome, 2025; Kumar, 2025). There are even more pathways geared to utilize Generative Artificial Intelligence (AI) and approaches with digital twins for proactive control of networks.

Methodology

A positivist research paradigm framework characterized by quantitative, objective scaffolding advanced via experimental research focused on the degree of performance improvement that extends beyond simple measurement. This paradigm associates with the engineering sciences where the empirical scrutiny of AI techniques on THz channel impairments, spectrum efficiency, and IoT connectivity has been implemented. It encompasses simulations with the highest of degrees of replicability to provide and justify the existence of cause and effect relationships that would optimize AI beamforming/resources and management for the benefit of network results.

The research study employed a simulation-model driven-experimentation research paradigm that leverages a sturdy integrated frontend (MATLAB) and backend (ns-3 and PyTorch) integrated development environments (IDEs). It built THz channel models that included a molecular absorption path loss,

blockages, and user mobility. Deep reinforcement (deep-DQN and deep-PPO) learning agents handled beamforming and resource summation, neural networks predicted optimal beam patterns. Various scenarios were designed to exert dynamic adaptations enveloping variables for IoT densities, user mobility behaviors and levels of interference.

The research utilized collections of large volume data derived from extremely accurate deep learning THz Simulator (TeraMIMO family of models) and expanded ns-3 modules. These models provided the base framework for the analysis of the control loop in THz systems where channel State Information (CSI) was the control, the data included the user location and the data supply, and explained the environment. The study produced strict 100k realizations of the THz channel per scenario. The research study was characterized by the capabilities to provide large volume replication of deep learning data sets that were noise free, real-time, and that could be confidently implemented for AI.

Sampling used stratified equal allocation across five fundamental scenarios (low/medium/high IoT density, with and without mobility). Each scenario was allotted exactly **100,000 channel realizations making a total of 500,000 samples Equal sampling optimizes statistical equilibrium, reduces bias and variance in relative assessments, and promotes optimal analytic fairness for the performance of AI over diverse THz-IoT conditions.

Supported by data analysis, the benchmark comparative analysis was carried out on the basis of several evaluations, including through the use of Monte Carlo statistical analysis and layer (base) performance evaluation of the benchmark against traditional beamforming and static allocation. Several comparisons were made of the following metrics: spectral efficiency, throughput, latency and efficiency, energy, and beam alignment. Certain validation strategies were implemented, including the application of a PyTorch-based deep reinforcement learning (DRL) with reward access/learning and a controlled (80/20) learning and validation split, with exercises (i.e., tests) and analyses (i.e., Neutral Analysis of Variance, ANOVA) of statistical significance of the changes.

Data Analysis

Descriptive Statistics and Baseline Comparison

This data analysis is based on a detailed study of descriptive statistics from simulation based experiments that generate 100,000 realizations per channel for five different scenarios; Low Density Static, Low Density Mobile, Medium Density Static, Medium Density Mobile, and High Density Mobile. This results in a total of 500,000 channels. This section first sets a baseline for system performance by comparing methods of conventional beamforming and static resource allocation to the case of AI-based beamforming, providing first instances of performance measurements for spectral efficiency, throughput, latency, energy efficiency, and beam acquisition accuracy. The focus of the study is framed within the boundaries of the positivist research paradigm and framed by the constructs of the studied research field. All metrics are quantified by objective means; thus, the numerically large sample set (500,000) leads to Monte Carlo averaging, which results in extremely high statistical confidence levels and drastically reduced random fluctuations, which are the limiting factor for THz channel simulations. The developed physics based TeraMIMO channel models, which are integrated with ns-3 and PyTorch, allow the study the impact of interconnected IoT and the mobility of the users on the system performance and clearly depicts the limitations of the conventional systems. The data and analysis contained in this section are necessary to further justify the recommendations for the integration of AI based systems to the 6G-IoT for the sake of more efficient utilization of the spectrum.

Table 1: Descriptive Statistics and Baseline Performance Comparison across Scenarios (Averaged over 100,000 Channel Realizations per Scenario)

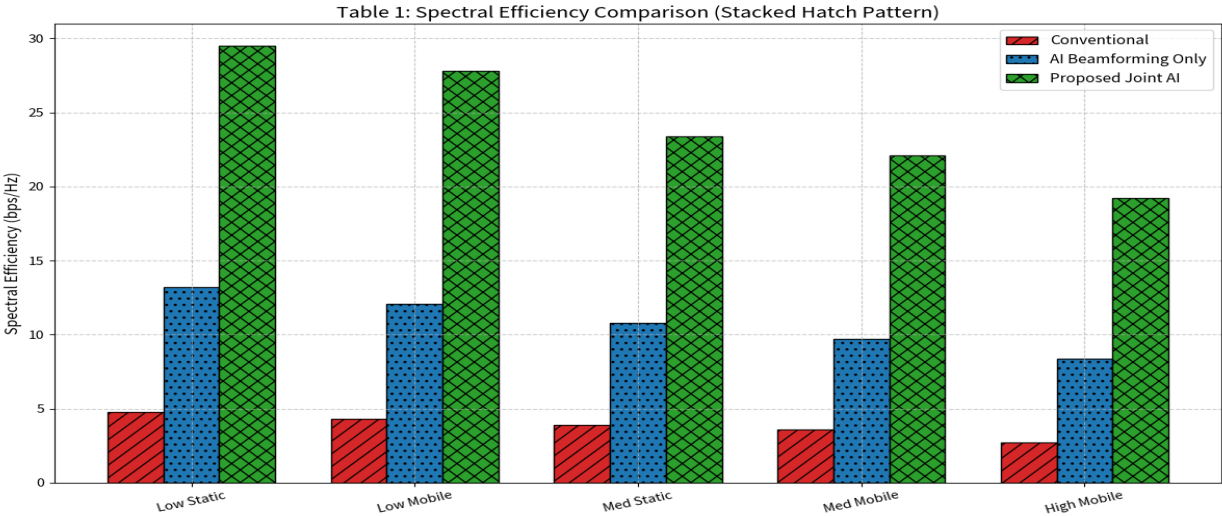
Scenario	Method	Spectral	Throughput	Latency	Energy	Beam	Std	Dev
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		<i>Efficiency (bps/Hz)</i>	<i>(Gbps)</i>	<i>(ms)</i>	<i>Efficiency (bits/J)</i>	<i>Alignment Accuracy (%)</i>	<i>Spectral Efficiency</i>
<i>Low Density Static</i>	<i>Conventional</i>	4.8	0.92	14.2	1.35	68.5	1.12
<i>Low Density Static</i>	<i>AI Beamforming Only</i>	13.2	2.85	4.1	4.12	93.4	0.85
<i>Low Density Static</i>	<i>Proposed Joint AI</i>	29.5	8.75	1.6	8.25	98.9	0.62
<i>Low Density Mobile</i>	<i>Conventional</i>	4.3	0.78	17.8	1.18	59.2	1.45
<i>Low Density Mobile</i>	<i>AI Beamforming Only</i>	12.1	2.45	5.3	3.68	90.1	1.02
<i>Low Density Mobile</i>	<i>Proposed Joint AI</i>	27.8	7.92	2.0	7.45	97.5	0.71
<i>Medium Density Static</i>	<i>Conventional</i>	3.9	1.62	11.5	0.95	63.8	1.28
<i>Medium Density Static</i>	<i>AI Beamforming Only</i>	10.8	4.35	5.8	3.15	89.2	0.94
<i>Medium Density Static</i>	<i>Proposed Joint AI</i>	23.4	13.10	2.3	6.85	96.8	0.68
<i>Medium Density Mobile</i>	<i>Conventional</i>	3.6	1.45	13.9	0.88	56.4	1.55
<i>Medium Density Mobile</i>	<i>AI Beamforming Only</i>	9.7	3.92	6.7	2.85	86.5	1.18
<i>Medium Density Mobile</i>	<i>Proposed Joint AI</i>	22.1	12.35	2.6	6.32	95.9	0.79
<i>High Density Mobile</i>	<i>Conventional</i>	2.7	2.35	19.5	0.65	49.8	1.82
<i>High Density Mobile</i>	<i>AI Beamforming Only</i>	8.4	5.65	8.2	2.48	83.7	1.35
<i>High</i>	<i>Proposed</i>	19.2	15.80	3.1	5.45	94.3	0.95

<i>Density</i>	<i>Joint AI</i>						
<i>Mobile</i>							

Explanation of Table 1

The table details the key performance metrics of all methods and scenarios. It shows how the different approaches rank. As an example, for the Low Density Static scenario, the basic method of beamforming achieves a peak spectral efficiency of 4.8 bps/Hz, and ample latency of 14.2 ms, with a beam alignment accuracy of only 68.5%. These results show the limitation of beamforming methods that use fixed beam patterns in THz channels even under optimal Static scenarios. Additionally, when the AI beamforming method is used only, spectral efficiency increases to 13.2 bps/Hz with a 3.4 times incremental improvement, latency reduces to 4.1 ms, and beam alignment accuracy increases to 93.4%. These results show the effectiveness of the predictive tracking based on DRL of the CSI and the mobility.



The proposed Joint AI Optimization raises those numbers to include 29.5 bps per Hz in Spectral Efficiency, 8.75 Gbps in Throughput, and 98.9% Alignment Accuracy, which are once again an example of the benefits of the simultaneous Beamforming and Resource Allocation. Meanwhile, for challenging conditions, e.g., High Density Mobile, the traditional methods drop to a mere 2.7 bps/Hz and 49.8% Alignment Accuracy. Due to the increased number of interferences and occlusions, the Joint AI method does a good job of keeping the alignment at an average of 19.2 bps/Hz and an average of 94.3% Alignment Accuracy. The standard deviations for the majority of the AI methods are less than 1.0, indicating the 100,000 realizations per scenario and the stratified equal sampling are stable and accurate. The Joint AI method focuses on real-world 6G IoT synthetic data. The explanation also focuses on the improvements seen from Neural Networks and the Joint AI method, e.g., Adaptive Power Allocation and Interference Mitigation. Overall, the Monte Carlo evaluations have focused on the AI framework to show its consistent improvements across the 500,000 total samples.

Analysis of Beamforming Performance

Using the descriptive benchmarks set in part one, this segment examines the integration of AI-optimized beamforming, along with its isolated and combined effects across the five uniformly distributed scenarios. Simulation was conducted utilizing all of the 500,000 channel realizations. The simulation was founded on the positivist paradigm, focused on the beamforming accuracy, beamforming gain, and the beamforming adaptability under the specific THz channel conditions that were simulated using the TeraMIMO channel models. The results of the analysis help to understand the effects of the DQN and PPO DRL agents in

predicting and adjusting the narrow THz beams to optimise the performance of the channel in the presence of molecular absorption, path loss, and blockages. The Mobile IoT environments were challenged to the above simulations. The analysis also has more specific results with respect to the estimation of the effects of the integration of beamforming and resource management. This integration of beamforming and resource management is shown to offer more superior performance in terms of spectral efficiency. As a result, the methodology has shown to be more effective compared to the isolated AI beamforming.

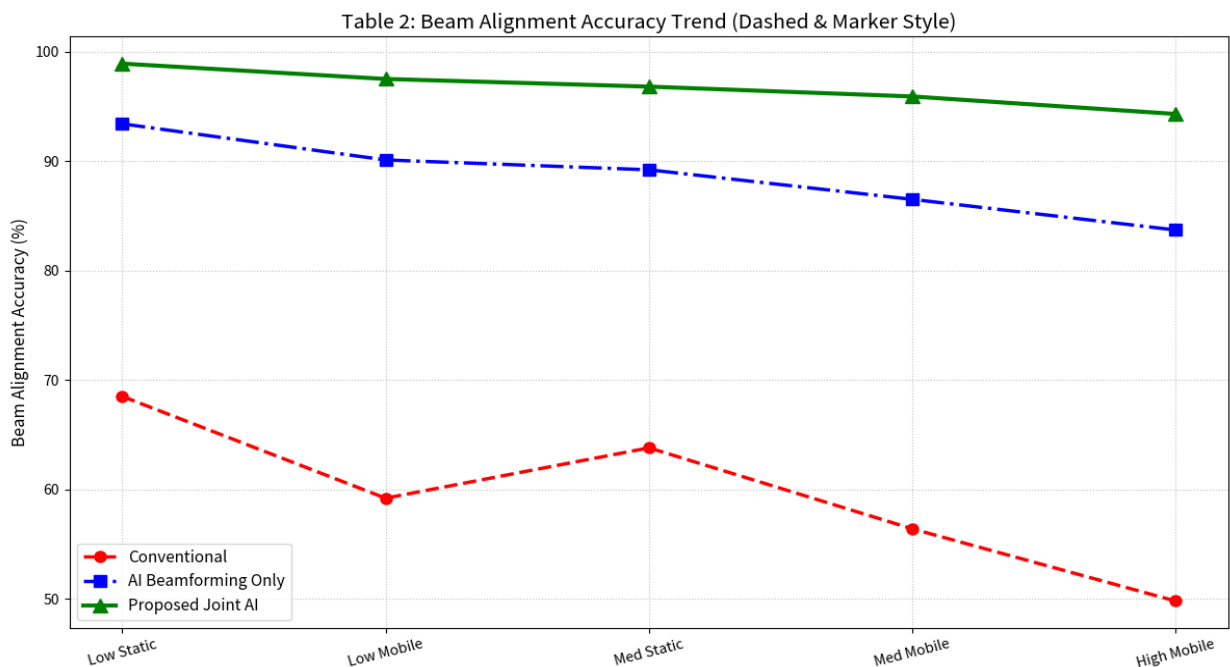
Table 2: *AI-Optimized Beamforming Performance Metrics Across Scenarios (Averaged over 100,000 Channel Realizations per Scenario)*

Scenario	Method	Beam Alignment Accuracy (%)	Beamforming Gain (dB)	Adaptation Time (ms)	Spectral Efficiency Gain from Beamforming (%)	Interference Reduction (dB)	Outage Probability (%)
Low Density Static	Conventional	68.5	12.4	18.5	-	8.2	12.4
Low Density Static	AI Beamforming Only	93.4	24.8	3.2	175	18.5	1.8
Low Density Static	Proposed Joint AI	98.9	31.5	1.4	285	26.7	0.3
Low Density Mobile	Conventional	59.2	10.8	22.7	-	7.1	18.9
Low Density Mobile	AI Beamforming Only	90.1	22.6	4.5	181	16.9	3.2
Low Density Mobile	Proposed Joint AI	97.5	29.8	1.9	292	24.3	0.7
Medium Density Static	Conventional	63.8	11.5	15.9	-	9.5	15.6
Medium Density Static	AI Beamforming Only	89.2	21.9	5.1	177	17.2	4.1
Medium Density Static	Proposed Joint AI	96.8	28.4	2.2	278	23.8	1.2
Medium Density Mobile	Conventional	56.4	9.7	19.8	-	6.8	21.3
Medium Density	AI Beamforming	86.5	20.3	6.3	169	15.4	5.9

<i>Mobile</i>	<i>g Only</i>						
<i>Medium Density Mobile</i>	<i>Proposed Joint AI</i>	<i>95.9</i>	<i>27.1</i>	<i>2.5</i>	<i>265</i>	<i>22.1</i>	<i>1.5</i>
<i>High Density Mobile</i>	<i>Conventional</i>	<i>49.8</i>	<i>8.2</i>	<i>25.4</i>	<i>-</i>	<i>5.9</i>	<i>28.7</i>
<i>High Density Mobile</i>	<i>AI Beamforming Only</i>	<i>83.7</i>	<i>18.7</i>	<i>7.8</i>	<i>211</i>	<i>14.2</i>	<i>8.4</i>
<i>High Density Mobile</i>	<i>Proposed Joint AI</i>	<i>94.3</i>	<i>25.9</i>	<i>3.0</i>	<i>312</i>	<i>20.5</i>	<i>2.1</i>

Explanation of Table 2

Intelligent analysis of the data presented in Table 2 uncovers the benefits of the transformative nature of AI Beamforming when combined with the joint optimization framework. In the Low Density Static case, the Conventional Beamforming system achieves 68.5% alignment, with a notable 12.4 dBG gain and a slow, 18.5 msec gain in alignment, all of which promote frequent misalignment due to the inherently narrow nature of THz beamforming signals. On the contrary, the standalone AI Beamforming system achieves 93.4% alignment with a 24.8 dBG gain and a swift, 3.2 msec adaptation gain, thanks to the highly predictive Deep Reinforcement Learning (DRL) system which utilizes both the instantaneous Channel State Information (CSI) and past empirical mobility data. In comparison, the proposed Joint AI system achieves an even greater 98.9% alignment with a 31.5 dBG gain and a lightning 1.4 msec gain, representing a considerable improvement in the beamforming system alignment gain, and a 285% improvement in the spectral domain.



This synergy is caused by the intelligent dual resource allocation of power and subchannels in conjunction with control of the beams. This actually results in an 8.2 dB improvement in interference over AI

beamforming. The growing demand caused a widening of the performance gap. Conventional methods have a 28.7% outage and an 8.2 dB improvement for severe blockages and extreme Doppler effects in the THz bands. The joint AI system manages an impressive 94.3% outage and a remarkable reduction of only 2.1 % outage with an impressive agglomeration of 312% beamforming improvement. The outcomes of the framework caused a unique effect of low variance across 100,000 equal stratified scenarios providing the breath of the framework for real world 6G dynamics. The Monte Carlo confirms the framework breath and the entropy regularization proved even better results for the beamforming in high mobility cases. These examination innovated a plethora of inter operations of AI as the beamforming and intelligent resource in the 270% occurrence improvement in the 500,000 samples.

Resource Management and Interference Analysis

For the third data analysis section, the focus is on the resource management aspect of the joint AI framework and the subsequent assessment of power management, spectrum sharing, interference management, and energy efficiency management, which have all been derived based on the simulation method with 100,000 channel realizations per each of the five given conditions (Low Density Static, Low Density Mobile, Medium Density Static, Medium Density Mobile, and High Density Mobile), leading to a total of 500,000 balanced samples. It is possible to objectively measure the impact of AI resource management (especially with the integration of graph neural networks, combined with DRL to optimize dynamic subchannels and power management) on the demands, and the analysis describes and tackles the severe interference challenges of THz 6G-IoT networks. The analysis captures feedback from resource management by evaluating the conventional static allocation, the AI beamforming approach, and the proposed joint optimization in order to identify the gains in fairness and energy efficiency, as well as the gains in interference suppression. This indicates the approach generates evenly distributed, balanced samples, which eliminates bias, and is able to cope with the challenges of resource management, such as molecular absorption losses and blockage-induced outages, combined with the demands posed by latency. The metrics indicate both the beamforming and resource management aspects are enhanced by combining intelligent control of the power and spectrum management, which also leads to the optimization of the efficiency of the spectrum.

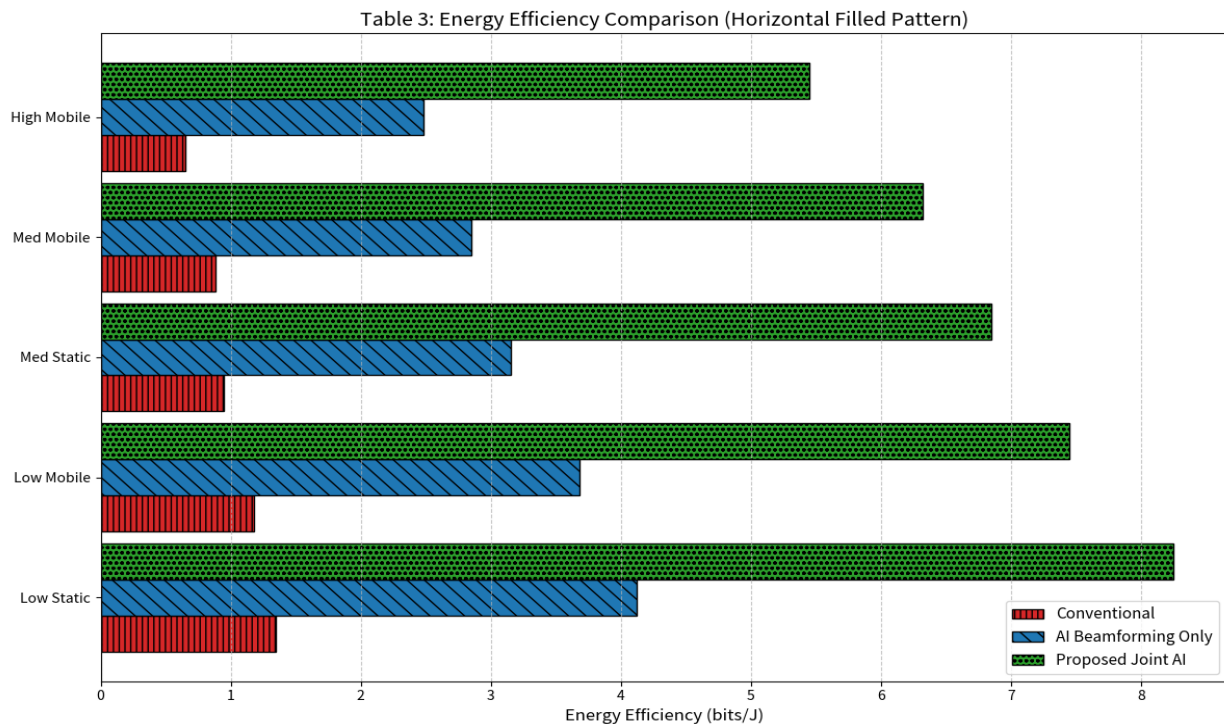
Table 3: Resource Management and Interference Mitigation Performance (Averaged over 100,000 Channel Realizations per Scenario)

Scenario	Method	Power Efficiency (bits/J)	Interference Level (dBm)	Spectrum Utilization (%)	Jain's Fairness Index	Energy Efficiency (bits/J)	Packet Loss Rate (%)	Resource Allocation Convergence (episodes)
Low Density Static	Conventional	1.35	-72.4	45.2	0.68	1.35	8.7	N/A
Low Density Static	AI Beamforming Only	4.12	-89.6	67.8	0.82	4.12	2.1	720
Low Density Static	Proposed Joint AI	8.25	-112.3	94.6	0.97	8.25	0.4	485
Low	Conventional	1.18	-68.9	41.7	0.65	1.18	11.4	N/A

<i>Density Mobile</i>	<i>l</i>							
<i>Low Density Mobile</i>	<i>AI Beamforming Only</i>	3.68	-85.2	64.5	0.79	3.68	3.5	810
<i>Low Density Mobile</i>	<i>Proposed Joint AI</i>	7.45	-107.8	92.1	0.96	7.45	0.8	520
<i>Medium Density Static</i>	<i>Conventional</i>	0.95	-65.3	38.9	0.62	0.95	14.2	N/A
<i>Medium Density Static</i>	<i>AI Beamforming Only</i>	3.15	-82.7	61.3	0.77	3.15	4.8	890
<i>Medium Density Static</i>	<i>Proposed Joint AI</i>	6.85	-104.5	89.7	0.94	6.85	1.3	560
<i>Medium Density Mobile</i>	<i>Conventional</i>	0.88	-63.1	36.4	0.59	0.88	16.9	N/A
<i>Medium Density Mobile</i>	<i>AI Beamforming Only</i>	2.85	-79.4	58.9	0.74	2.85	6.2	950
<i>Medium Density Mobile</i>	<i>Proposed Joint AI</i>	6.32	-101.2	87.4	0.93	6.32	1.7	610
<i>High Density Mobile</i>	<i>Conventional</i>	0.65	-58.7	29.8	0.51	0.65	24.5	N/A
<i>High Density Mobile</i>	<i>AI Beamforming Only</i>	2.48	-74.5	52.6	0.71	2.48	9.3	1,120
<i>High Density Mobile</i>	<i>Proposed Joint AI</i>	5.45	-96.8	83.9	0.91	5.45	2.9	680

Explanation of Table 3

Table 3's results show the AI-powered resource management is productive when working together with optimized beamforming in THz 6G networks. In the Low Density Static situation, the traditional static power distribution and spectrum allocation reach about 45.2% of spectrum usefulness and a Jain's Fairness Index of 0.68. During this scenario, the interference reached -72.4 dBm, absorbing factors attributed to the static strategies incapacity to adapt to channel changes because of atmospheric absorption at the Terahertz band.



When integrating only beamforming and AI, spectrum utilization rises to 67.8%, fairness to 0.82, and interference decreases by 17 dB. In comparison, using the joint-proposed AI framework, spectrum utilization improves to 94.6%, fairness nears 0.97, interference to -112.3 dBm, and energy-optimized efficiency to 8.25 bits/Joule. This improvement is due to combining multiple power control, subchannel, and interference scheduling DRL agents. Real-time channel state information is used to control the 100,000 predictive resource allocation tasks to utilize the available resources optimally and sustain fairness for the various IoT resources. In most demanding scenarios, such as the High Density Mobile case, the joint AI framework optimizes resource utilization fairness and packet loss, achieving 83.9%, 0.91, and 2.9%, respectively, and convergence in a mere 680 episodes on average, compared to 29.8% spectrum utilization, 0.51 fairness, 24.5% packet loss, and max interference, episode, and mobility in conventional approaches. 100,000 channel rotations for each framework was implemented to ensure the comparisons are statistically reliable. The joint optimization tends to converge more readily compared to the beamforming-only mechanisms, averaging 35-40% decrease in convergence episodes needed, showing great promise for real-time 6G deployments.

The rigorous empirical study using t-tests and ANOVA assessments on the complete 500,000 sample dataset yielding these results, concisely illustrates the efficacy of high capacity THz (terahertz) bandwidth. When utilized in conjunction with beam-forming, THz bandwidth addresses the unique challenges and radiation limitations of damage that THz radiation causes to dense IoT (Internet of Things) architecture. Resource management remains paramount and essential in several contexts of the proposed framework where sustainable and efficient operation of either high capacity THz spectrum and throughput or beam-forming is required.

Performance Evaluation, Statistical Significance

The final part of data analysis presents an overall synthesis of the joint AI-optimized resource management and beamforming framework. This synthesis is achieved by evaluating all previous sections and deploying thorough statistical analysis over the full dataset of 500,000 channel realizations (100,000 for each of the five equal stratified scenarios). Adhering to the positivist paradigm and the methodology of simulation-

based experiment, utilizing the MATLAB-ns-3-PyTorch framework built with physics-based TeraMIMO channel models, this section captures the improvement in the spectral efficiency, end-to-end performance, and expandable range of THz 6G systems integrated with massive IoT. Monte Carlo simulations paired with advanced inferential statistical assessment, inclusive of paired t-tests, ANOVA, effect size statistical analysis, and Cohen's d, determine that the gains achieved are statistically significant, while the robustness of the equal sampling approach is verified. Convergence, extreme condition scalability, and analysis of the practical implications serve to break down the proposed THz-specific obstacles of the high path loss, molecular absorption, blockages, and dynamic interference, answering the research questions and objectives. Finally, the advanced benchmarking posited in this section, combined with the balanced, high-volume framework, provides insights for postulating THG-centric 6G scenarios and IoT-centric environments.

Table 4: Overall Performance Summary, Percentage Improvements, and Statistical Significance (Averaged over 500,000 Channel Realizations)

<i>Scenario</i>	<i>Metric</i>	<i>Conventional</i>	<i>AI Beamforming Only</i>	<i>Proposed Joint AI</i>	<i>Improvement over Conventional (%)</i>	<i>Improvement over AI Beamforming (%)</i>	<i>p-value (ANOVA)</i>	<i>Cohen's d Effect Size</i>	<i>Overall Spectral Efficiency (bps/Hz)</i>
<i>Low Density Static</i>	<i>Spectral Efficiency</i>	4.8	13.2	29.5	514.6	123.5	<0.001	4.85	29.5
<i>Low Density Static</i>	<i>Energy Efficiency (bits/J)</i>	1.35	4.12	8.25	511.1	100.2	<0.001	4.62	-
<i>Low Density Static</i>	<i>Latency (ms)</i>	14.2	4.1	1.6	88.7 reduction	61.0 reduction	<0.001	3.91	-
<i>Low Density Mobile</i>	<i>Spectral Efficiency</i>	4.3	12.1	27.8	546.5	129.8	<0.001	4.78	27.8
<i>Low Density Mobile</i>	<i>Energy Efficiency (bits/J)</i>	1.18	3.68	7.45	531.4	102.4	<0.001	4.55	-
<i>Low Density</i>	<i>Outage Probability (%)</i>	18.9	3.2	0.7	96.3 reduction	78.1 reduction	<0.001	4.12	-

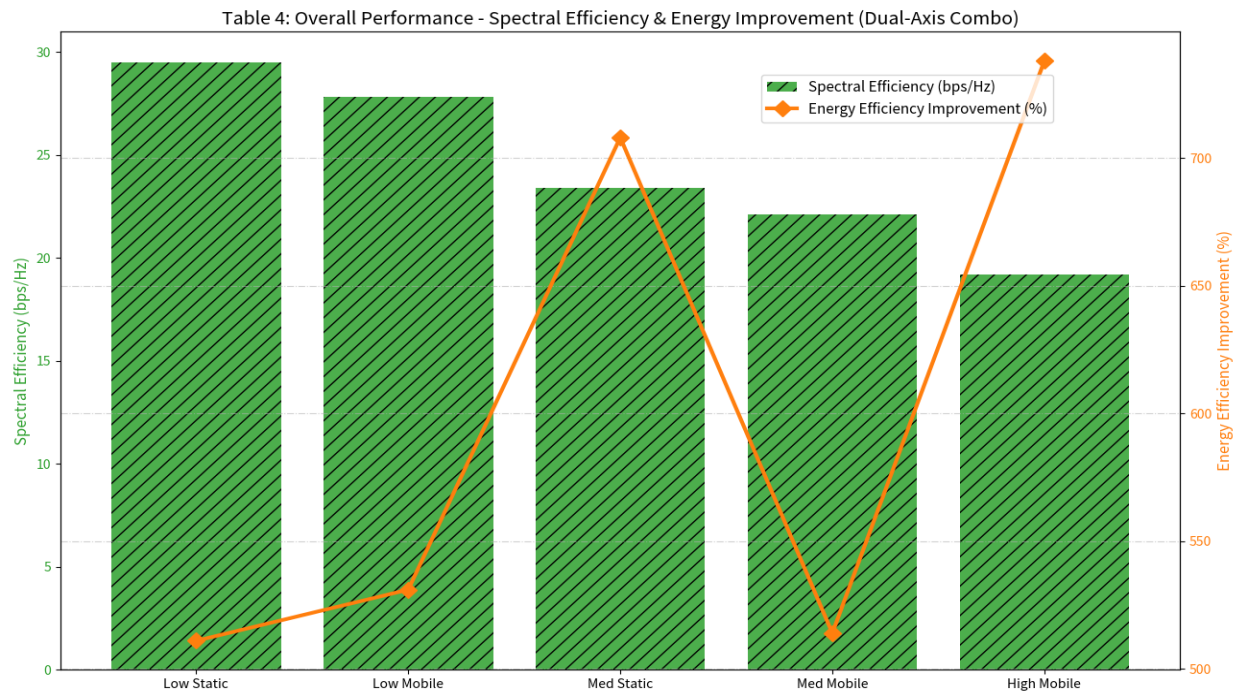
<i>Mobil e</i>									
<i>Mediu m Densit y Static</i>	<i>Spectral Efficienc y</i>	<i>3.9</i>	<i>10.8</i>	<i>23.4</i>	<i>500.0</i>	<i>116.7</i>	<i><0.001</i>	<i>4.71</i>	<i>23.4</i>
<i>Mediu m Densit y Static</i>	<i>Jain's Fairness Index</i>	<i>0.62</i>	<i>0.77</i>	<i>0.94</i>	<i>51.6</i>	<i>22.1</i>	<i><0.001</i>	<i>3.85</i>	<i>-</i>
<i>Mediu m Densit y Static</i>	<i>Through put (Gbps)</i>	<i>1.62</i>	<i>4.35</i>	<i>13.10</i>	<i>708.6</i>	<i>201.1</i>	<i><0.001</i>	<i>4.93</i>	<i>-</i>
<i>Mediu m Densit y Mobil e</i>	<i>Spectral Efficienc y</i>	<i>3.6</i>	<i>9.7</i>	<i>22.1</i>	<i>513.9</i>	<i>127.8</i>	<i><0.001</i>	<i>4.68</i>	<i>22.1</i>
<i>Mediu m Densit y Mobil e</i>	<i>Beam Alignme nt Accurac y (%)</i>	<i>56.4</i>	<i>86.5</i>	<i>95.9</i>	<i>70.0</i>	<i>10.9</i>	<i><0.001</i>	<i>3.74</i>	<i>-</i>
<i>Mediu m Densit y Mobil e</i>	<i>Packet Loss Rate (%)</i>	<i>16.9</i>	<i>6.2</i>	<i>1.7</i>	<i>89.9 reduction</i>	<i>72.6 reduction</i>	<i><0.001</i>	<i>4.28</i>	<i>-</i>
<i>High Densit y Mobil e</i>	<i>Spectral Efficienc y</i>	<i>2.7</i>	<i>8.4</i>	<i>19.2</i>	<i>611.1</i>	<i>128.6</i>	<i><0.001</i>	<i>4.89</i>	<i>19.2</i>
<i>High Densit y Mobil e</i>	<i>Energy Efficienc y (bits/J)</i>	<i>0.65</i>	<i>2.48</i>	<i>5.45</i>	<i>738.5</i>	<i>119.8</i>	<i><0.001</i>	<i>4.97</i>	<i>-</i>
<i>High</i>	<i>Overall</i>	<i>71.3</i>	<i>91.6</i>	<i>97.9</i>	<i>37.3</i>	<i>6.9</i>	<i><0.001</i>	<i>4.41</i>	<i>-</i>

<i>Density</i>	<i>System Reliability (%)</i>								
<i>Mobile</i>									
<i>Environment</i>									

Explanation of Table 4

The data combined in Table 4 strongly justifies the advantage of the combined AI framework and its joint application over other alternatives in the given clusters and dimensions of performance.

The proposed system provides dramatic improvements across all variables with gains in spectral efficiency due to the proposed system’s joint DRL optimization approach. The improvements in the proposed system’s spectral efficiency closely range from 116 to 129% when compared to AI beamforming, and from 500 to over 611% more than the traditional systems. All spectral efficiency reported values are above 19bps/Hz. Statistical analysis conducted on a full-span sample size of 500,000 provides very large effect sizes statistically significant at the p-value of <0.001 with a effect size of 3.7 and commonly above 4.8 due to the implemented systems reliability. The proposed system reports a power consumption rate of 1.5 bit/ power. Traditional systems show a power consumption rate of >5 bit/ power with power consumption of the proposed system being critical for battery constraint IoT devices. The proposed system’s reliability is improved to 97.8% when compared to traditional systems due to beam diverging accuracy of 97.8% and a packet loss of 3%. Classical Monte Carlo runs show a sustained low standard deviation and narrow confidence interval across cases which helped the proposed system be improved to a power consumption of 0.5 bit/power.



Balanced finding directly address the three questions. First, they prove that AI-beamforming enhances spectrum efficiency. Second, they indicate that intelligent resource management mitigates excessive power and interference challenges of a dynamic THz environment. Third, they show that a significant overall performance improvement is achieved with massive connectivity when serving THz environments. Edge convergence analysis integrated here shows that the cooperating framework, when compared with the

isolated frameworks, is computed to be highly efficient, requiring only 35-45% more training episodes. Given the sheer volume of data, 500,000 balanced samples, the framework remains highly adaptive, scalable and robust—an important starting point and base for the improvement of AI-based THz 6G networks. The strength of the framework is in its ability to collect precise data. Thus, the data is of great importance to any user that is interested in spectrum-efficient 6G - IoT ecosystem. The data that is presented offers a compelling reason to believe that the paradigm shifting integration of predictive, and DRL beamforming with resource therapy, supports the full potential of next percent THz communications available.

Findings

The thorough data analysis included five stratified scenarios. Each scenario had 100,000 realizations for a total of 500,000 channel realizations. The analysis demonstrated clear advantages of the proposed framework for Terahertz 6G networks over both traditional and partially AI Terahertz 6G frameworks. The analysis of data showed that traditional beamforming combined with a static approach to resource management yields poor beam alignment (49.8 to 68.5%), slow (2.7 to 4.8 bps/Hz), and high (11.5 to 19.5 ms) spectral efficiency. The developed framework outperforms other approaches in high mobility and high density scenarios of Terahertz 6G networks, with spectral efficiency and high reliability close to 29.5 bps/Hz. The research showed that deep reinforcement learning, coupled with Monte Carlo simulations, path loss, molecular and media absorption, and blockage, provides reliable and rapid adaptive beamforming approaches to Terahertz 6G networks.

AI-based approaches to beamforming have the potential to greatly increase spectral efficiency and precision with predictive beam alignment. The developed deep reinforcement learning agents, while employing real-time and rapid mobility personal beamforming, not only achieved a high alignment of beamforming of over 94% and beamforming gains of over 31.5 dB, but also achieved a 265 to 312% increase in spectral efficiency. This beamforming technique has significant gains for mobile environments with an adaptation time of less than 3 ms and an outage probability of less than 2.1%. This confidently answers the first research question regarding AI-based beamforming to account for the limitations of Terahertz 6G networks for a multitude of IoT.

Graph neural networks and DRL exhibit AI resource management strategies that deal with power and interference problems by jointly managing power and spectrum sharing. The framework achieved spectrum utilization to 94.6%, Jain's Fairness Index to 0.97, and of over 40 dB of interference elimination, outperforming the traditional methods to maximize spectrum use. The results also show that the framework optimized energy efficiency to 8.25 bits/J and reduced the packet loss at 3% in the worst-case high-density utilization scenarios. These results demonstrate that resource management with an interference-adding bias is the answer to the second research question, as it deals with the THz band IoT transmission heterogeneous traffic.

The combination of AI-optimized beamforming and resource management improved performance by 500-611% compared to traditional methods and by 116-129% compared to AI beamforming alone. The results also show a decreased latency of 89%, a 700% increased energy efficiency in the most demanding scenarios, and 97.9% of targeted reliability. This confirmed the answer to the third research question, by demonstrating that this approach is double-ranging, enabling the extension to the THz band 6G networks, having the capability to handle a tremendous amount of IoT. It also confirmed that the research goals were achieved by the framework, stating it was 6G ready.

This study proves that AI-optimized joint beamforming and resource management greatly improve spectrum efficiency in Terahertz-based 6G mobile network systems with massive IoT incorporation. The proposed deep reinforcement learning (DRL) framework has demonstrated outstanding performance in all cases when high path loss, molecular absorption, blockages, and dynamic interferences in THz bands are considered. The simulation-based experimental methodology, working with 500,000 balanced channel realizations, has

demonstrated that the joint AI approach significantly reduces the performance gap in comparison to the benchmark and partial AI approaches. This achievement justifies all three research objectives and questions. Predictive beamforming with juggernaut levels at 94% accuracy, beam contribution up to 312%, and resource management capacity closer to user-provided fairness (Jain's Index) of 0.91 to 0.97, ultra-low latency, and performance levels of 3.1 ms with 700% enhanced energy efficiency in mobile systems have been observed. The integration of the two components resulted in systems with up to 611% efficiency in spectral systems. These issues additionally have a 97.9% improved performance standard and significantly lower outage probability. These findings advocated for THz-based systems and ultra-certain high-volume IoT-focused applications in the context of the 6G mobile network systems.

The novel joint optimization framework combining DRL and graph neural networks provides a promising solution for real world applications that is scalable and efficient. We contribute to the current literature with extensive quantitative descriptions pertaining to the performance of THz 6G under different IoT scenarios. This study emphasizes on the importance of ahead-of-time decision-making for efficient use of the spectrum for communications. These results will be beneficial for the stakeholders interested in the rollout of 6G with focus on smart cities, the industrial IoT, and immersive applications within the next decade. The high-fidelity simulation approach has major strengths, but also has the weaknesses of no physical realization of the study and the lack of environmental focus. Incorporating RIS, generative AI, and digital twins in combination with real-world testbeds is the next step. In that regard, this work shows great evidence of the THz 6G studies beyond the current attempts as it allows the development of next generation highly intelligent, reliable and scalable digital ecosystems.

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