

Original Article

Predictive Beam Management with Spatio-Temporal Hyper Networks and Reinforcement Intelligence for Sustainable Massive MIMO Architectures

G. Kanagavalli¹, P. Dhinakar²

^{1,2}Department of ECE, Bharath Institute of Higher Education and Research, Tamil Nadu, India.

¹Corresponding Author : kanagavalli.ece@bharathuniv.ac.in

Received: 02 July 2026

Revised: 12 September 2026

Accepted: 24 September 2026

Published: 28 October 2026

Abstract - Massive MIMO is the basis of current 5G and future 6G wireless networks, with antenna gain significant spectral efficiency and network capacity, but is unable to support dynamic environments due to computational complexity, power consumption and CSI overhead. The research presents a single adaptive and energy-efficient beam management system, including hybrid analogue-digital beamforming and advanced intelligence based on learning. This system extends Deep Reinforcement Learning to optimize beams in real-time, graph-based learning to optimize beams selectively by topology, neuro-symbolic policy optimization to predict and study control, and spatio-temporal forecasting using hypernetworks to CSI, which cuts feedback costs by a major factor. The proposed framework reduces redundant CSI updates by dynamically changing beam patterns based on user movement, interference, as well as the changes in traffic conditions, and provides strong signals quality and low-latency adaptation. The main innovation is the combination design of prediction beam adaptation and energy aware CSI management. The performance of simulations shows that spectral efficiency, power and computing scalability have been significantly improved, making the solution a viable and future-proof architecture of intelligent massive MIMO network.

Keywords - Beam management, Channel state information overhead, Energy efficiency, Mobility awareness, Network scalability, Spectral efficiency.

1. Introduction

Massive Multiple-Input Multiple-Output (Massive MIMO) has become a pillar of technology in modern-day wireless communication infrastructure, the foundation of the performance goals of 5G networks and the architecture of the future 6G ecosystem. Massive MIMO allows the unprecedented spectral efficiency, reliability, and network capacity advantages support by equipping base stations with massive antenna arrays, and serving multiple users within the same time frequency resources. The gains are essential in countering the explosion in increases of mobile data traffic, the rise of heterogeneous devices, and the highly quality-of-service standards of new applications, including immersive extended reality customer requirements, ultra-reliable low-latency networks, and massive machine-like network demands. Nevertheless, with a larger antenna size and active network attracting dynamism, the actual implementation of the Massive MIMO suffers severe problems, which are not conventional signal processing aspects.

Acquisition and management of the Channel State Information (CSI) is one of the most urgent problems. Beamforming and spatial multiplexing performance in

Massive MIMO systems are dependent in an extremely tight way on the quality of CSI, but the overhead associated with producing timely and accurate channel estimates is high. Repeated CSI feedback and pilot transmission, in addition to absorbing precious spectral resources, also results in more energy being consumed at both the network and user equipment level. This can be further worsened in situations that are characterized by high user mobility, heavy concentrations, and rapidly changing interference Conditions when CSI needs to be updated frequently and be obsolete. With the development of networks to ultra-dense and highly adaptive networks, traditional CSI acquisition methods are beginning to fail at the balance between performance, latency, and energy efficiency.

Another bottleneck is that of beamforming complexity. Though fully digital beamforming can provide finer-grained control and performance and is available, it requires a radio-frequency chain per antenna element, which is prohibitively expensive to acquire and to use in large arrays. The less expensive hybrid analog. However, hybrid beamforming also poses challenges in its design, such as non-convex optimization, non-phase resolution and requires smart



coordination between the analog and digital worlds. Such architecture needs methods of beam management which are adaptive and can achieve deals in the face of limited hardware, but quite quickly to the changing environment.

With the issue of sustainability and the cause and cost of deployment of a large-scale network, sustainability has become a performance parameter in modern and future wireless systems. Unscrupulously optimized constructions, Massive MIMO base stations have large energy requirement due to their many antennas and heavy signal processing demands. In addition to transmission energy, computational energy related to beam selection, CSI processing and real-time optimization are factors that play a significant role in the total energy amount. With the networks shifting towards the stages of intelligent and autonomous functioning, it is important that the improvement in performance should not be only achieved at the cost of unsustainable energy requirements. This requires a systematic approach where the management of beams, fielding of CSI and learning-based intelligence are to be developed in liaison with the energy awareness as a first-class goal.

New possibilities in machine learning have created fresh opportunities when considering the complexity and adaptivity needs of Massive MIMO systems. Data-driven models, specifically deep learning and reinforcement learning, have shown that it has a promising potential in the representation of nonlinear relationships, interaction learning by engaging with the environment and real-time decision-making in uncertain situations. With beamforming, learning-based methods allow the system to deduce useful pattern of the beam in direct proportion to what it observes, without the use of either explicit channel models or extensive beamforming search algorithms. In particular, deep reinforcement learning provides a more natural and simple structure of making sequential decisions, which means that beam management policies can develop in response to long-term performance goals like throughput, latency, and energy usage.

Although it has potential, the purely data-driven methods have drawbacks connected to interpretability, generalization, and scalability. Wireless networks have structural properties of topology, spatial relations, and time dynamics that are not necessarily effectively used by generic learning frameworks. The graph-aware methods of learning offer a principled way of imbuing the learning process with network topology and user-base station connections, which allows adaptation more thriving and topology-sensitive. Graph-based models may mirror meditations, or interferences and spatial dependencies of users, beams or access points in a graph and their interaction in an edge that is especially important in dense Massive MIMO processes.

Additionally, black-box characteristics of deep learning compel the question of control, reliability and deployment in

communication systems where the safety and service of the communication is at stake. Neuro-symbolic learning has been proposed as a potentially valuable paradigm to deal with such issues by allowing the expressiveness of neural networks with the structure and interpretability of symbolic reasoning. Neuro-symbolic policy optimization in beam management can incorporate domain knowledge, constraints, and energy-awareness policies into the learning process, producing not only a working policy but also a more open and predictable one. This model of intelligent hybrid facilitates an active and interpretable control, something necessary in the management of collection network behavior on a long-term scale of operation.

The other important aspect of intelligence behind the Massive MIMO is the ability to predict the channel dynamics. Predictive models also allow forecasting the future behavior of the channel based on historical and contextual data, instead of responding to immediate updates of CSI. Models Hypernetwork-based spatio-temporal learning architectures (hypernetworks) are especially efficient in this task because they can dynamically change model parameters dynamically over time, space, and users. Best CSI prediction helps to anticipate beam adaptation, limits the occurrence of explicit feedback and rectifies effect of feedback delay. The networks will acquire reduced latency and enhanced resilience to the changes of mobility and traffic conditions by shifting to predictive operation instead of reactive operation. It is in this larger context that the combined design of beam adaptation and CSI management is an open and difficult challenge.

The current solution methodologies assume that beamforming optimization and CSI acquisition are different layers, which results in poor trade-offs and unnecessary overhead. The requirement to consolidate coherent frameworks that bring together learning-based beam control procedures with smart CSI management, and clearly taking into consideration the energy dissipation, and scaling of computation, is on the increase. These structures should work reasonably in the hybrid beamforming conditions, utilize the network structure and adjust to the conditions in the real world and do not passively generate too much overhead.

The work deals with these issues and proposes an adaptive and energy-efficient beam management model of Massive MIMO systems that integrates hybrid analog digital beamforming and numerous layers of learning-based intelligence. The framework is expected to reduce the extraneous CSI updates by using deep reinforcement learning to manage real-time beam optimization, a graph-based method with topology sensitivity of adaptive control, neuro-symbolic optimization of control policies, and forecasting of the CSI by a spatio-temporal hypernetwork, and maintain high signal quality and low-latency responsiveness. High values of joint predictive beam adaptation and energy-constrained CSI control make the suggested scheme stand out compared with

existing literature and are consistent with sustainability and intelligence objectives of a new wireless network.

With the development of wireless systems to 6G and beyond, where it is extremely densified, pervasive intelligence, and highly energy-constrained, the inclusion of adaptive learning and effective beam control will be necessary. Existing studies on beamforming, power allocation, CSI optimization, hybrid architectures, RIS-assisted transmission, deep learning and reinforcement learning, as well as energy-efficient Massive MIMO. But these techniques normally solve some problems regarding beam management, CSI prediction, network topology, and energy optimization, respectively. To date, limited work has integrated deep reinforcement learning, graph-based learning, neuro-symbolic reasoning, and spatio-temporal hypernetwork-based CSI prediction for adaptive beam management for interpretable, predictive and energy-aware beam management.

2. Literature Survey

The two problems of beamforming and power optimization of cell-free MIMO systems are aimed at improving user fairness through the joint design of beamforming vectors and power allocation strategies. These methods deal with the inter-user interference and non-homogeneous channel conditions so that the users have equal quality of service. Cell-free architectures can be used to achieve greater spectral efficiency and better connectivity by means of distributed antennas coupled with coordinated transmission. Convex and non-convex methods are usually used to optimize system throughput in order to create fairness in frameworks. Cell-free MIMO offers [1] a variety of possibilities in the next-generation wireless communications because the integration of the advanced signal processing algorithms allows dynamically adapting the algorithms to different network conditions.

The 5G massive MIMO with the broad beamforming technology is expected to enhance network coverage, as well as connections with users in high-density networks. Base stations have an ability to serve many users at the same time since wide-angle beams are generated, making the process of tracking users much less precise. The technique adds robustness of the network to mobility as well as channel changes, in addition to reducing the complexity of beam management. Wide-beam designs are also employed, especially in urban implementations [2], whereby visual access is reduced. Implementation strategies usually include hybrid analog-digital beamforming in order to compromise on equipment efficiency and signal quality. Broad beamforming helps in enhancing smooth 5G connectivity and spectral use of high-capacity in a situation.

The Cell-free massive MIMO systems, Integrated Access and Backhaul (IAB) solution offers an affordable network

densification approach. IAB simplifies the deployment process by providing the same infrastructure to connect access links and backhaul connectivity, and improves spectral efficiency. Such networks exploit associated transmission and active resource management to accommodate large user concentrations and small latency. Beamforming plans [3] are modified to serve user equipment as well as relay data simultaneously in links in the backhaul, and this makes the connectivity smooth. The insertion of IAB in cell-free infrastructures enables line-linear increase in network and better reliability, which is more appropriate in urban and high-traffic locations where conventional backhaul systems can be limited.

Ultra-massive MIMO Beamforming technologies of terahertz communications would provide very high data rates and low-latency connections of the wireless networks of the future. Directional transmission is facilitated with the help of advanced antenna arrays and channel estimation technologies and can be used to combat path loss and atmospheric attenuation [4] typical of terahertz frequencies. Analog-digital analogue beamforming, Hybrid, Hybrid Analogue-digital precision. This approach improves spectral efficiency and network capacity, and solves the challenge of ultra-massive arrays. Optimization models take into account energy efficiency and resiliency in the face of hardware degradation. These technologies enable high-resolution spatial multiplexing, which is useful in new applications like holographic communications, autonomous systems, and immersive extended reality. Terahertz beamforming is one of the important enablers of 6G and beyond.

The techniques of machine learning used on mammoth MIMO systems improve the performance and flexibility of the system. Learning methods are used to estimate the channel conditions and interference patterns, which optimize the beamforming, power allocation, and user scheduling. The reinforcement learning model, supervised, and unsupervised learning models assist in decreasing the amount of computations and enhancing energy utilization [5] at the expense of spectral efficiency. It has found applications in predictive beam management, anomaly detection and real-time resource optimization. The lack of data, generalization of the model and hardware restrictions are common performance constraints. The future issues include applying AI-based strategies to the implementation of realistic networks and providing reliability, scalability, and low-latency functionality, which will lead to intelligent massive MIMO networks.

The second problem is learning energy-efficient transmitter configurations of the gigantic MIMO beamforming, which is aimed at minimizing power consumption and preserving the high data rates. With the utilization of machine learning algorithms, systems can adjust the transmission parameters according to the changing

channel conditions [6] and user requirements. They are reinforcement learning to maximize precoding policies, channel prediction of neural networks and fast adaptation of meta-learning. These approaches balance energy efficiency and spectral performance to reduce inter-user interference as well as hardware constraints. Experimental evidence indicates that with major energy consumption savings, throughput is not compromised. These would be especially applicable to sustainable network design in 5G or later, where massive MIMO deployments with power-efficient concerns are paramount to the provision of large amounts of connectivity. In the massive MIMO system, user selection techniques deal with issues of increasing the number of served users. With efficient selection algorithms, system throughput, fairness and interference are optimized because sets of users are selected dynamically to be transmitted concurrently. Methods are channel quality-based scheduling, machine learning-based prediction [7] and greedy scheduling or optimization-based scheduling to maximize the capacity at low complexity. The techniques decrease pilot contamination and computation. User selection policies improve the performance, scalability and energy efficiency of massive MIMO systems by targeting users with good channel conditions or quality-of-service needs: their use allows high-density urban networks with 5G networks in control.

Directional transmission + Non-orthogonal multiple access Angle-domain hybrid beamforming in mmWave massive MIMO-NOMA systems optimizes spectral efficiency. Angle-domain processing allows an accurate beam steering and separating between users by taking advantage of the sparse appearance of mmWave channels. Hybrid beamforming [8] combines digital and analog elements to compromise between price of the hardware and fidelity of the signal. NOMA enables different users to share the same time-frequency resource, enhancing the network capacity and equity. It is important to optimise the power allocation and beam patterns in order to reduce the inter-user interference and maximise sum-rate performance. Such integration is essential to dense urban deployment and can be used in next-generation wireless networks to maintain high throughput and low-latency applications.

Strong tensor representation of heterogeneous beamforming deals with issues that are generated by inaccurate channel state information in multi-user MIMO systems. The decomposition techniques can be used to represent the channel matrices in tensors, so each spatial, temporal, and frequency aspect may be de-noised in order to produce a more precise beamforming. This reduces the error brought about by inaccuracy in estimation and time delay [9] caused by feedback, which enhances signal quality and reduction of interference. Optimization models make sure that the system is robust to a wide variety of user situations and a wide variety of network configurations. TC techniques permit adaptive low-complexity beamforming (large-scale MIMO

arrays). It is especially useful when the channels are dynamic and highly mobile, providing reliability and spectral efficiency in the next-generation wireless systems.

6G ultra-massive MIMO hybrid beamforming. Prototyping CNN-LSTM-based fusion separation deep neural networks allows the prototyping of advanced channel estimation, and precoding does not use cluttering. Convolutional layers identify the spatial correlation, whereas LSTM layers recognize the temporal correlations, which increase the accuracy in prediction in dynamic environments. Separation in Fusion mechanisms. The multi-user signal is combined [10] in the fuse separation mechanisms to perform effective beamforming and decrease the interference.

This combination deep learning method improves spectral performance, a capability of channel variability, and system capacity. These architectures can facilitate complex ultra-massive MIMO deployments of hundreds of antennas, lowering the complexity of computation than that of conventional techniques. These are important in 6G that expects extremely fast data rate, low latency, and consistent multi-user connectivity applications in dense networks.

Multi-objective optimization of hybrid beamforming in achievable capacity gains in practical full-duplex massive MIMO systems. Full-duplex is capable of simultaneous reality of both transmission and reception and doubles spectral efficiency, but provides self-interference problems. The hybrid beamforming designs are optimal in this way that they are able to optimize both analog and digital precoders to prevent the interference and to maximize [11] the throughput in the system. Multi-objective optimization is used in view of trade-offs between energy efficiency, signal to interference plus noise ratio, and hardware constraints. Practical applications solve channel estimation errors, hardware impairment and mobility of users. The solutions allow scaled, high-capability wireless networks that can be used in next-generation applications that need ultra-reliable and low-latency communications with enormous connectivity in dense urban and industrial setting.

Environmental exposure assessment is in simplified formats of electromagnetic field measurements around 5G massive MIMO base stations. These approaches give reliable estimates of the exposure of humans to electromagnetic fields since they use standardized measurement systems and non-complex methods of analysis. Factors such as spatial distribution [12], beamforming patterns, as well as temporal variations of transmitted signals are considered. Streamlined protocols ease the complexity of measurements and enhance reproducibility, and do not violate regulatory specifications. These are necessary techniques in urban deployments that have numerous base stations that are situated near each other. These findings endorse safety network architecture and health protection of the population, so the well-being of magnificent

MIMO and 5G technology can be in great harmony with negligible environmental and biological harm.

The results of manifold-based optimization of RIS-enhanced massive MIMO systems achieve higher spectral efficiency and reliability through the simultaneous optimization of reconfigurable intelligent surfaces and beamforming solutions. Manifold optimization methods make high-dimensional parameter space and non-convex constraints highly and efficiently amenable by exploiting the geometry of complex signal space. The elements of RIS dynamically [13] control the wireless channel, enhancing coverage, alleviating interference, and allowing transmission using less power. The models of optimizations take into account transmitter as well as RIS structures in multi-user communication scenarios. The methods allow the heavy-traffic environment and highly mobile conditions of operation. Combining the RIS with the massive MIMO and manifold algorithms is one of the most important steps toward versatile, intelligent, and high-capacity wireless networks.

Directional beam outdoor massive MIMO testbeds offer a realistic process of testing the high capacity wireless communication methods. These testbeds are used in conjunction with sophisticated arrays of antennas, fine beamforming, and realistic outdoor conditions to test system operation concerning mobility issues, contexts, and propagation. Hardware-based hardware calibration, software-based software-defined control and throughput based on coverage [14], latency and coverage measurement can be used in implementation. Outcomes serve to guide the development of beamforming algorithms, scheduling of users and network optimization. They need such testbeds to help to translate the theoretical models into deployable solutions and build 5G and beyond networks that are robust, efficient, and able to support dense urban and rural environments where the directional connectivity is reliable.

Interference exploitation in 1-bit massive MIMO precoding It is based on deep learning techniques to exploit hardware constraints and achieve the best performance of the system. Through strategically devising neural network models predicting and utilizing the patterns of interference, 1-bit precoding has the potential of closing the gap between the performance [15] of higher resolutions systems with reduced power and complexity.

These techniques include optimizations of transmit signals through learning and reduction of quantization effects. These techniques are efficient spectrally, energy saving, and large-scale MIMO implementations. Integration between deep learning and low-resolution precoding is specifically pertinent to the cost-sensitive and energy-limited situations that allow to enable the scalable and viable deployments of massive-scale precoding-based MIMO networks in 5G and future 6G systems.

The arrays of scalable modular antennas handle the flexibility of deployment and scalability. Incremental addition of the antenna units in a network can be supported by modular designs, which can support network densification without significant underlying infrastructure reorganization. The innovations are the compact design, high-isolation and beamforming functions to sustain spectral efficiency and minimize [16] mutual coupling. Such challenges include the issues of calibration, complexity of signal processing, and consistency in the performance of modules. Such designs allow customized coverage, flexible capacity and easy maintenance. Scalable modular arrays are specifically useful within urban, dense settings with traffic loads that vary. They contribute to the effective deployment of the massive MIMO application, which allows the 5G networks to be expanded effectively at low costs and enhances their connectivity and reliability.

Massive MIMO, data compression jointly with STAR-RIS, Massive MIMO combined with data compression techniques significantly boosts the fronthaul capacity in cloud radio access links. Smart surface pixels change wireless channels so that signal qualities and coverage are enhanced. Massive MIMO offers data fronthaul bandwidth savings, as well as enormous spatial multiplexing margins. Optimization models aim to achieve the optimum [17] sum-rate using realistic constraints, such as front-haul capacity and power usage. These solutions permit optimal utilization of resources and allow low-latency communications, which are helpful in dense urban implementations and in high-need services. The merger of RIS aided massive MIMO and advanced fronthaul design is one of the major steps towards scalable and high-performance cloud-based wireless networks.

Shaping a covariance over the Riemannian manifolds can usefully improve the massive MIMO communication by maximizing spatial correlation structure. The use of covariance matrices on Riemannian manifolds makes it possible to deal with both positive-definite constraints and non-linear optimization efficiently, enhancing the accuracy of beamforming and precoding. This technique eliminates inter-user interference [18], improves signal quality, and provides multi-user transmission. Optimization on manifold increases convergence and reduces computational complexity over the conventional Euclidean optimization. They can be used in estimating channel as well as resource allocation and managing interference in large-scale MIMO networks. Covariance shaping gives a mathematically sound platform to leverage on spatial statistics, to harness high-capacity, effective wireless communication in dense urban and high-mobility conditions.

The 6G wireless systems are being developed through the integration of hybrid networks, artificial intelligence, ultra-massive Multiple-Input Multiple-Output (MIMO), terahertz frequencies, and the use of FBMC modulations. Hybrid

network structures have adopted the use of several radio access technologies to enhance coverage and reliability. Artificial intelligence allows smart management of resources, beamforming, and interference. The ultra-massive MIMO and terahertz frequency ranges can provide very high data rates, and FBMC can provide [19] flexibility of spectrum utilisation. Hardware complexity, channel estimation and energy efficiency are some of the challenges. End-to-end integration guarantees low latency and high spectral efficiency and emerging application cases, including immersive reality, autonomous systems, and ultra-reliable communications. The highly demanding specifications of the future 6G networks have been met through all of these technologies.

Deep reinforcement-learned optimization of IRS-NOMA-aided cell-free massive MIMO systems is superior to spectral efficiency and user fairness. An intelligent reflecting surface is used to dynamically adjust the characteristics of the channels with the aim of improving signal quality and coverage. NOMA enables multiple users to be served by the same resources [20], whereas deep reinforcement learning modifies beamforming and power allocation methods to current network features. The trade-offs are those in the area of throughput, fairness, and energy efficiency, which the optimization process makes to accommodate dynamic user distributions and channel variability. The method will facilitate scalable, intelligent, and efficient wireless communication in the congested city setting. IRS, NOMA and cell-free massive MIMO with learning-based optimization are the combination that will be a major solution towards a high-capacity network in the next generation.

The work concentrates on smart beam control of the millimeter-wave massive MIMO systems with multiple users in parallel. Neural networks are used to identify the best selections of beam in the dynamic channel environments, which save the time of productive beam searches. The method enhances the accuracy in beam alignment and system throughput [21] by finding spatial and temporal channel characteristics. The results of the simulations reveal high spectral efficacy and low latency over the traditional beam management methods. The work notes the appropriateness of data-informed models of managing the demands of dense user spatial and rapidly varying mmWave channels that neural-network-based beam management can be a solution to the next-generation wireless networks.

This work introduces a miniature antenna array with ultra-high-frequency massive MIMO base stations with a wide-angle beam scan. The instrument focuses on a smaller physical size and yet high gain and constant radiation performance over [22] a broad field of scan. The antenna enables convenient beam steering by maximizing the arrangement of elements, feed structures to enable future ultra-dense networks. Performance Measures indicate that it has low side lobe levels and has regularities across wide

angular spans. The proposed array can solve the practical deployment challenges, including space limits and hardware complexity, to provide a feasible hardware solution to the future base station that must have flexible and reliable beam-steering.

This work explores the optimization of beam integration in MIMO system with an approach that is hybrid, that is, the integration of both predictive neural networks with bio-inspired optimization. Recurrent prediction models are used to predict the behavior of the temporal beam, and an ant colony optimization algorithm is used to optimize beam [23] integration strategies. This combination is used to make the beam draw proactively and delve effectively into the search space. Convergence speed and beamforming performance are improved, as shown by the results compared to the use of traditional optimization methods. This method is especially useful in dynamic conditions where the conditions in the channels change quickly, showing how the use of prediction-based intelligence can be used to supplement heuristic optimization of robust and adaptive beam management.

This work tackles the issue of beam training in very large-scale MIMO systems; systems whose spatial non-stationarity is spatial in nature. The problem with traditional beam training techniques is that different channel properties can occur between the array, hence making the training methods inefficient. The suggested method is capable of adapting beam training techniques [24] to the case of a spatially dependent channel behavior, minimizing the training overheads without compromising accuracy. Simulation and analytical findings indicate that the technique enhances the performance of the beam in relation to alignment and reliability of the linkages. The work offers the understanding of viable beam training design in selecting next-generation large-aperture arrays in which traditional assumptions of stationarity cannot be taken.

The work dwells on multibeam phased array systems in satellite-based massive MIMO communications, utilizing the frequency dispersion characteristics. Frequency-dependent beam steering is employed in order to produce multiple beams at minimal expense [25], as opposed to complex hardware. The method allows flexible coverage and better utilization of the spectrum of satellite links. The performance testing has confirmed that it is possible to serve a number of users at the same time and with minimal complexity of the system. It is topical, especially in the context of high-throughput satellite systems, whereby enormous MIMO methods are able to add value to the capacity, coverage terms and capabilities in managing interference.

This work gives an introduction to massive MIMO as one of the basic technologies to support the current and future communication networks. It talks of some of the fundamental concepts, such as large-scale use of antennas, spatial multiplexing, and beamforming and how they influence

capacity, energy efficiency, and reliability. Channel estimation [26], the complexity of hardware implications, and interference issues are considered to be the key implementation issues. The discussion points out that massive MIMO facilitates high-quality services and provisions the level of performance of the latest and future wireless standards. The work is a brief source on the strategic value of massive MIMO in the development of future communication ecosystems.

The work suggests a QR-based precoding framework to uses multiuser massive MIMO to improve its performance by expanding the null space. The precoder successfully reduces inter-user interference and leaves the computationally efficient method of matrix factorization, which lives by the spirit of exploitation. The approach enables [27] wide extension of the null space, which enhances resiliency in saturating user aura.

Analytical analyses indicate that there are performance improvements with regard to signal quality and reduction of interference relative to traditional precoding schemes. The method is quite appropriate to the systems that need low complexity but efficient multiuser transmission strategies.

This work presents a three-dimensional beam mapping model, which is efficient in terms of energy usage and quality-of-service provision at stacked traffic levels. The system operates with dynamically responding beam patterns as a spatial demand varies to lower power usage and ensure user performance guarantees.

The suggested optimization [28] plan takes both vertical and horizontal beam size into account, allowing the fine-grained coverage adjustment. The simulation findings verify a huge saving of energy and constant service quality at times of traffic surge. The work explores the relevance of smart beam control in the sustainable use of large type of MIMO networks in serving various and time-varying user requirements.

The work investigates the issue of feasibility of antenna arrays during multi-band use in high-frequency base-station massive MIMO systems. It examines design issues in supporting more than one frequency band in an array architecture, by considering performance trade-offs between coupling, bandwidth and radiation efficiency.

The findings demonstrate [29] that well modified arrays can be effectively used to support multi-band transmission without the unreasonable duplication of hardware. The latter is an essential feature of future networks that should be able to use different spectrum allocations to be flexible in deployment and better utilization of new high-frequency resources.

This work introduces an interference coordination model around radio environment maps of massive MIMO cellular

networks. The system can be used to coordinate the strategies of transmission between the neighboring cells with the help of the spatial information of the interference. The method enhances the awareness of interferences and allows [30] making more informed beamforming and scheduling decision-making.

Existing studies focus on optimizing a single aspect of beamforming, power allocation, RIS/NOMA, user selection, interference management, and learning-based beam control in massive MIMO, which, however, often involve independent optimization and rely on frequent CSI update.

To perform energy-aware beam adaptation, there is limited work that combines real-time deep reinforcement learning, topology-aware graph learning, neuro-symbolic policy optimization, and spatio-temporal hypernetwork forecasting. The proposed framework fills this gap by providing predictive, selective and low overhead beam management in the presence of dynamically changing network conditions.

3. Methodology

The suggested methodology provides a single, learning-based beam management system to the massive MIMO systems with an explicit design of providing the balance between spectral efficiency, energy consumption, and CSI overhead in a highly dynamic network environment. The strategy is closely pipeline coupled with channel awareness, beam adaptation and energy control not developed as independent modules but as a co-evolution.

This methodology commences by abstraction of the huge MIMO setting as a dynamic decision environment to reflect user mobility, user traffic need, interference coupling factors, and hardware factors. The physical-layer on which scale and power efficiency is guaranteed is hybrid analog, digital beamforming.

It is based on this foundation that various learning paradigms are combined, such as deep reinforcement learning in online beam selection, graph-conscious learning in topology-sensitive coordination, neuro-symbolic reasoning in policy interpretability and stability and spatio-temporal hypernetworks in predicting CSI.

The individual components are meant to share small latent representations instead of raw CSI, which allows a massive reduction of signaling overhead. The concept of energy-awareness is integrated into all stages by activating the RF chains and predictive beam updates adaptively.

The entire methodology follows in a step-wise but interdependent process to guarantee strength, reduced latency and long-life cycles when implementing the next generation massive MIMO systems as shown in Figure 1.

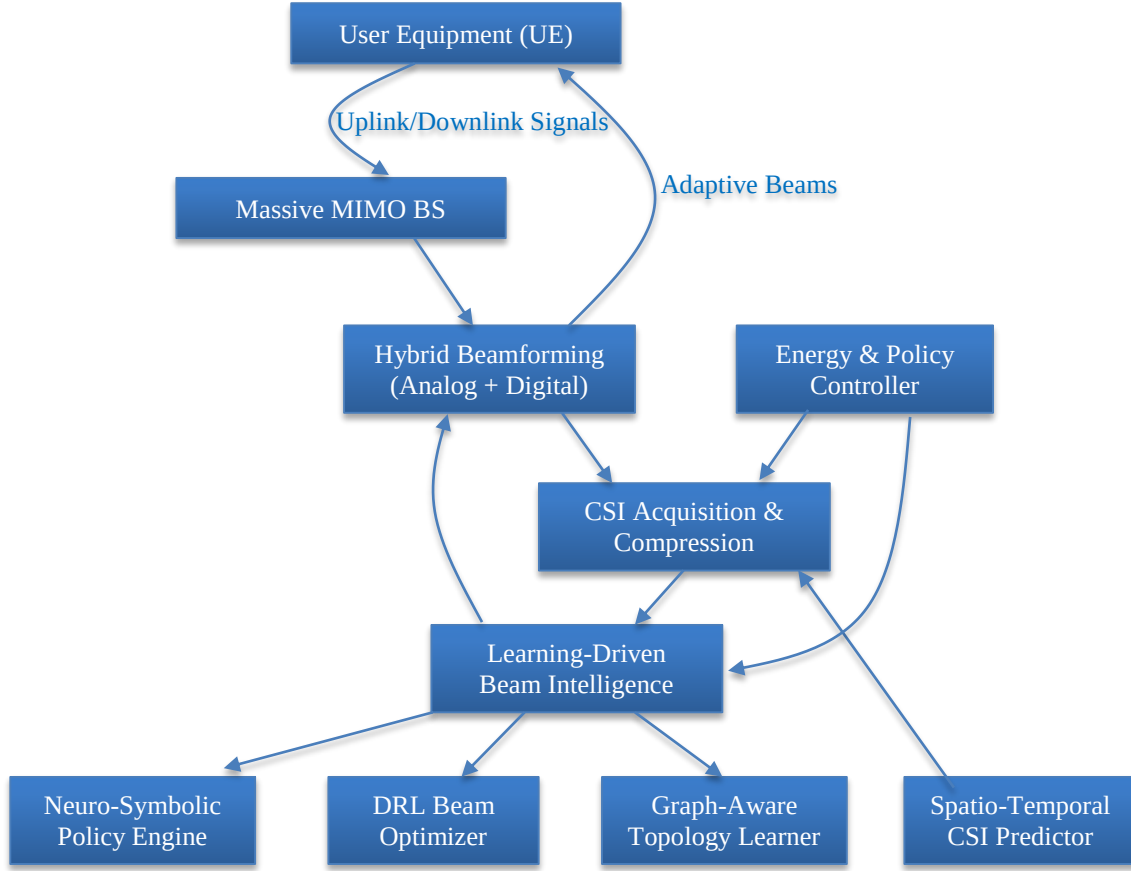


Fig. 1 System architecture

3.1. System Modeling and Problem Formulation

The huge MIMO system is assumed to be a multi-user and multi-cell setup which has a base station with the large antenna array that can be used to serve mobile users in when time-varying channels are present. Hybrid beamforming is used, a digital precoder based on low dimension jointly work with analog phase-shifter network. Partially complete CSI, the position of users, interference graphs, traffic demand, energy-constrained System state.

The beam management problem is stated as a sequential optimization problem that can maximize spectral efficiency in the long run and minimise energy use and CSI feedback overhead cost. This is a trade-off that is explicitly represented in the form of a weighted utility functionality which adapts with time as network conditions vary. The formulation allows learning-based agents to make rational reasoning on a delayed and imperfect CSI, as opposed to perfect channel observability. The optimization problem is formulated as

$$\max_{\pi} \mathbb{E} \left[\sum_{t=0}^T \gamma^t (R_t - \lambda P_t - \mu C_t) \right] \quad (1)$$

where π denotes the beam control policy, R_t represents spectral efficiency, P_t denotes power consumption, C_t captures

CSI overhead, and γ is the discount factor. This formulation provides the foundation for learning-driven beam adaptation.

3.2. Hybrid Analog-Digital Beamforming Design

Hybrid beamforming is being embraced so that the complexity of the hardware is minimized without severely restricting the flexibility of beamforming. The methodology breaks down the overall precoding matrix into an analog beamformer that picks up coarse spatial directions and a digital beamformer that picks up user-specific multiplexing. The analog beamformer is held back by constant-modulator phase shifters and the digital stage is dynamically adjusted on the basis of trained channel representations. The design does not use instantaneous CSI, but rather uses predicted and compressed channel embeddings that are provided by upper-level learning modules. The separation allows hundreds of antennas to operate in a scaled manner. Transmitted signal is modeled as effective as

$$\mathbf{x}(t) = \mathbf{F}_{\text{RF}}(t) \mathbf{F}_{\text{BB}}(t) \mathbf{s}(t) \quad (2)$$

where $\mathbf{F}_{\text{RF}}$ is the analog beamforming matrix, $\mathbf{F}_{\text{BB}}$ is the digital precoder, and $\mathbf{s}(t)$ is the symbol vector. Energy efficiency is enhanced by selectively activating RF chains based on traffic demand and predicted channel quality. This

hybrid structure acts as the execution layer for all subsequent learning-driven beam decisions.

3.3. Deep Reinforcement Learning for Beam Optimization

Deep reinforcement learning is used in order to allow beam adaptation in real-time in an uncertain environment. The beam management problem is mathematically represented as a Markov decision making in which the agent monitors the partial system state and chooses beam choices that regulate analog and digital precoders. Function of the reward is added with spectral efficiency, energy consumption, and CSI signaling cost that promotes balanced long term operations. A deep neural network is included so as to give the way to the optimal action-value functionalities enabling the agent to generalize over a wide range of channel circumstances and movement patterns. With online communication with the environment, one can always adapt without directly modeling channels. The learning goal is stated as follows.

$$Q^*(s, a) = \mathbb{E} \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') \mid s_t = s, a_t = a \right] \quad (3)$$

Where s and a denote system states and beam actions. Experience replays and target networks stabilize training, while adaptive exploration ensures responsiveness to sudden network changes. This module forms the core decision engine of the framework.

3.4. Graph-Aware Learning for Topology-Sensitive Adaptation

Graph-aware learning is used to model inter-user interference and spatial correlations as an explicit representation of network topology. The graph nodes represent users and base stations, with the edges performing the functions to encode the strength of interference and the proximity in space. Graph neural networks are run on these structures to produce embeddings which capture both local and global patterns of interference. These embeddings control the adaptation of the beam, allowing coordination of user decisions and minimizing combating and enhancing equity. Graph convolution operation is used to aggregate information within a neighborhood as

$$H^{(l+1)} = \sigma(D^{-1/2} A D^{-1/2} H^{(l)} W^{(l)}) \quad (4)$$

Where A is the adjacency matrix, D is the degree matrix, and $H^{(l)}$ represents node features. This framework simultaneously provides robust beam coordination with no centralized exchange of CSI by integrating topology-awareness into the learning process, providing a direct solution to scalability problems in dense deployments.

3.5. Neuro-Symbolic Policy Optimization

Neuro-symbolic learning is included into the beam control policy to improve its interpretability and stability. Neural policy updates of a neural policy include symbolic

rules that are based on domain knowledge, like mobility thresholds or interference constraints. This mixed solution will avoid unsafe or energy-implicit behaviors but have the flexibility. Symbolic constraints are soft regularizers that are applied to policy optimization and direct the learning process to physically relevant solutions. The objective of constrained optimization is as follows:

$$\min_{\theta} \mathcal{L}_{RL}(\theta) + \beta \sum_k \|\phi_k(\pi_{\theta})\|^2 \quad (5)$$

Where ϕ_k represents symbolic constraints and β controls their influence. Through this integration, convergence rate is enhanced, policy swings are decreased and explainable beam choices can be made which are vital to operational trust in the future intelligent networks.

3.6. Spatio-Temporal Hypernetwork-based CSI Forecasting

Spatio-temporal hypernetworks are used to give out a prediction of channel using spatial temporal prediction models which are conditioned by the mobility and traffic context. Rather than a complete CSI is transmitted, the system predicts future channel conditions on a short-term basis, which the system allows proactive beam updates. The hypernetwork accordingly generates the hypernetwork parameters of a base predictor in a fashion which would adapt appropriately to changes in the environment. The predicted CSI evolves as

$$\hat{H}_{t+1} = f_{\omega(z_t)}(\hat{H}_t) \quad (6)$$

Where $\omega(z_t)$ denotes hypernetwork-generated parameters. The method minimizes the number of feedback drastically whilst preserving beam accuracy. Finally, joint design of predictive beam adaptation and CSI management energy efficiency is completed by deciding when prediction confidence drops and new CSI is needed via energy-aware predictive triggering mechanisms.

4. Result and Discussion

The simulation of the proposed unified adaptive and energy-efficient beam management framework is performed with elaborate simulations that simulate dense multi-user massive MIMO deployments in highly dynamic conditions. The findings are always able to show significant improvements in spectral efficiency, power usage, CSI overhead, and computational scalability when predictive intelligence, topology awareness and energy aware learning are implemented.

The results are read to further explain their interpretation in the discussion that ensues and how each of the observed improvements would be directly attributed to the choices of the methodological design and the reaction of the framework to the different network stress factors which include mobility, density of interference as well as change of traffic.

The former group of findings dwells on spectral efficiency operation under varying user mobility patterns. The proposed framework performs much better in terms of sum-rate performance than conventional hybrid beamforming with fixed codebooks and periodic CSI feedback. This enhancement is further exaggerated with rise in user mobility which points to the advantage of predictive beam adaptation. The system eliminates the misalignment losses which are normally experienced in fast-fading conditions by predicting channel evolution at a shorter time and acting proactively to reorient the beam directions. Although the learning-based approach yields observable improvements even in pedestrian mobility, where existing approaches have already reached acceptable performance, this can be attributed to the tendency to use temporal correlations which are ignored by other approaches.

Topology-aware learning is also shown to be highly interfering on the case of dense interference scenarios. The number of users in active service increases, and inter-beam interference becomes the leading throughput factor of the system. The graph-conscious learning sub-module allows the structure to make implicit beam decisions, resulting in much more spatially orthogonal transmissions with no centralized interference cancellation. This leads to a smoother tradeoff in spectral efficiency to an increase in network load whereas the sharp performance reduction with a crossing of interference thresholds occurs when using a baseline scheme.

Table 1 gives the average spectral efficiency during various mobility regimes, which clearly shows the soundness in the proposed framework.

Table 1. Average spectral efficiency comparison (bps/Hz)

Mobility Scenario	Conventional Hybrid BF	DRL-based BF	Proposed Framework
Static Users	18.4	21.1	23.6
Pedestrian	15.2	18.7	22.1
Vehicular	10.9	14.3	19.5

The energy efficiency is one of the core features of the given design, and the outcomes prove that smart beam control could decrease the power decisions substantially without the negative impact on the performance. The framework reduces transmission and processing energy by dynamically enabling RF chains and restricting the transmission of unwarranted CSI updates.

The proposed system uses the resources of hardware in real time unlike the fixed hybrid beamforming architectures which maintain full activity of hardware resources when traffic demand is lower than the system. This results in massive savings in low traffic times and elimination of over-provisioning in peak times.

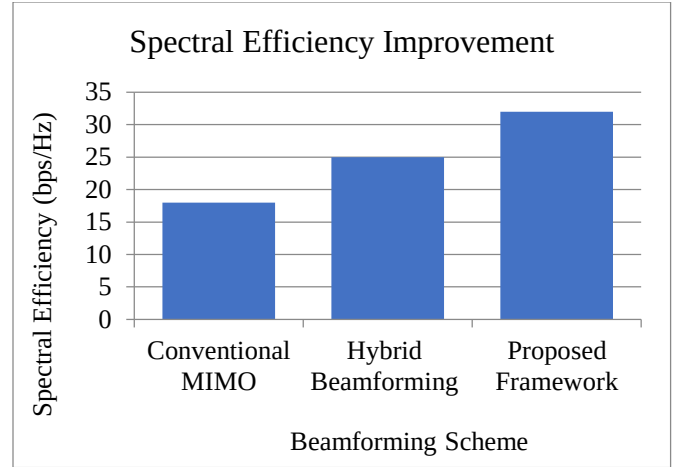


Fig. 2 Spectral efficiency improvement

In Figure 2, it compares the values of spectral efficiency of three beamforming schemes. Traditional MIMO attains 18 bps/Hz which denotes constrained adaptability and increased interference. Hybrid beamforming is beneficial as it enhances the 25 bps/Hz so that RF chains complexity is partially reduced and the beam alignment improved. The proposed coordinated framework shows a maximum spectral efficiency of 32 bps/Hz, and it indicates the advantage of adaptive beam control and predictive CSI control developed by the learning process in order to utilize better opportunities of the spatial multiplexing advantages over the past methods.

The advantages of CSI management consciousness of energy can be seen especially when looking at the overhead of feedback. Conventional systems are based on repeated updates of CSI to control beam positioning with large uplink signaling and processing expense. Conversely, the spatio-temporal hypernetwork-based CSI forecasting module enables the system to be functional with a reduced number of updates. The saving of energy will not be corrupted by the misalignment of the beams unless the prediction confidence decreases below a certain threshold, when feedback is activated. This discriminative feedback approach is directly converted to a shorter latency and higher uplink capacity presence.

In Table 2, it presents the mean power consumption of various traffic loads that are being experienced and shows that there would be a saving in power consumptions through the proposed structure.

Table 2. Average base station power consumption (Watts)

Traffic Load	Conventional Hybrid BF	Energy-Aware BF	Proposed Framework
Low	410	335	280
Medium	520	455	360
High	690	640	515

Another important consideration of massive MIMO systems that is likely to be challenged as the number of antennas and the density of users increases is computational scalability. Its findings demonstrate that the suggested framework is more graceful to scale than optimization-based beamforming methods. Whereas classical algorithms respond exponentially to the size of the number of antennas, the learning-based method is near-linear beyond the initial amount of training. This characteristic is what renders the framework especially appealing to future massively large arrays implied by 6G networks.

Performance in latency also brings out the merit of decision making that is based on learning. The response times are low even when the conditions are changing quite fast because the decisions of the beam are produced during neural inference without employing the iterative optimization formulation.

This is necessary in order to support ultra reliable low latency communication services whose delayed beam updates can seriously harm quality of service. Through the addition of neuro-symbolic constraints the stable latency can also be achieved because the policy cannot behave erratically and hence cause sudden reduction in performance.

Table 3 shows the mean beam adaptation latency with varying systems sizes, validating the attributes of the low-latency optimality of the proposed system.

Table 3. Beam adaptation latency (milliseconds)

Number of Antennas	Optimization-Based BF	DRL-Based BF	Proposed Framework
64	4.8	2.1	1.6
128	9.5	2.4	1.9
256	18.2	2.9	2.2

Neuro-symbolic policy optimization comes into prominence especially when performance of the system at extreme conditions is considered. Agents driven solely by a data-driven reinforcement learning can be unpredictable in the exploration behavior, especially in situations that require sudden jumps in mobility, or an abrupt or stressful upsurge of traffic. Symbolic constraint additions, which are backed by bodily and operational regulations, are what make the beam choice stay within the acceptable levels of safety and energy utilization. It leads to more harmonious performance curves and quicker recuperation of brief upheavals, supporting the reasonability of the framework in the deployment in the real world.

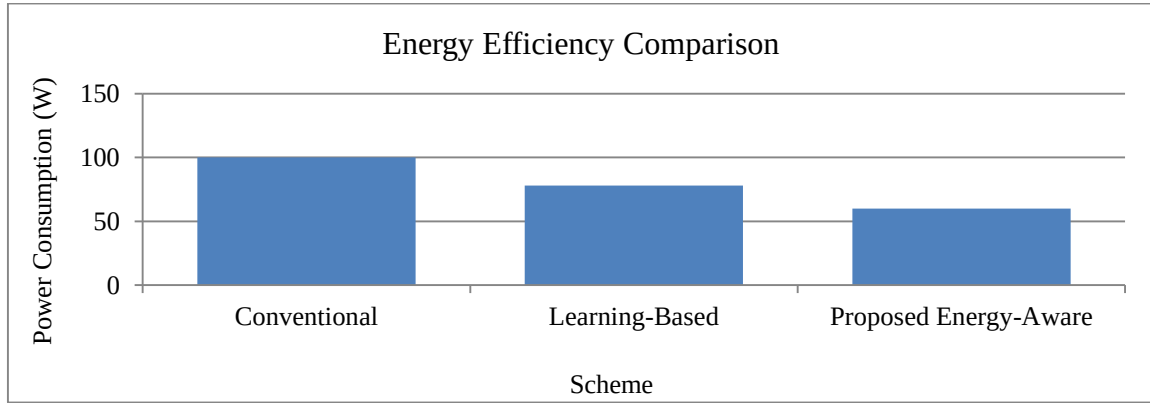


Fig. 3 Energy efficiency comparison

In Figure 3, the power consumption in relation to various beam management strategies. The traditional model uses 100 W since CSI is regularly updated and expensive to compute power. The approach based on learning consumes less power of 78 W providing adaptive decision making.

The framework suggested can further reduce the consumption to 60 W simultaneously optimizing beam adaptation and CSI prediction with a significant difference in energy usage and the performance of the system in dynamic network conditions. The comparison of the performance variance in response to sudden mobility differentiation is presented in Table 4 that demonstrates the resilience of the proposed framework.

Table 4. Spectral efficiency variance under mobility spikes

Scheme	Variance (bps/Hz)
Conventional Hybrid BF	14.7
DRL-Only BF	9.2
Proposed Framework	4.6

In Figure 4, it is an evaluation of the end-to-end latency with an increase in user mobility. Latency in the baseline system increases rapidly, as increases by 5ms at 0km/h up to 25ms at 40km/h because beam misalignment occurs frequently. The framework suggested exhibits a less rapid change, 4 ms to 13ms, which points to a high-quality real-time beam adjustment. It validates the mobility assistance with predictive and learning-based beam control.

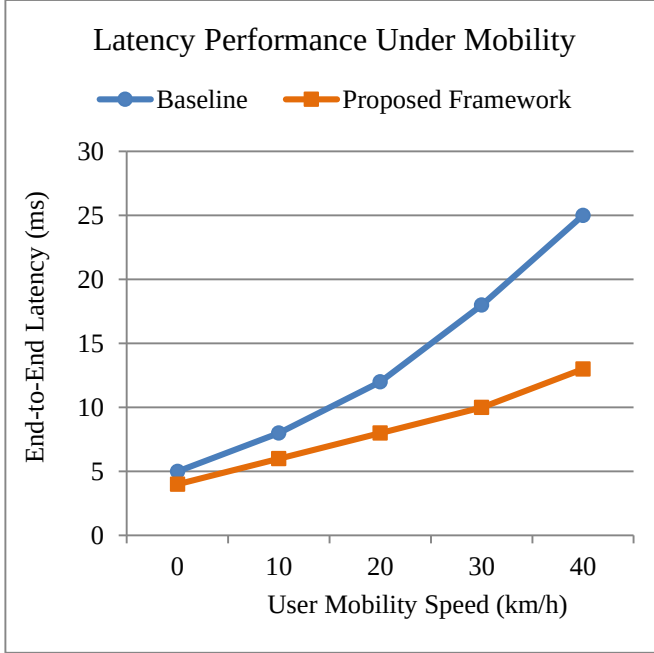


Fig. 4 Latency performance under mobility

CSI forecasting effectiveness is also confirmed through prediction accuracy analysis and influence on beam alignment. This predictor is the hypernetwork-based predictor which is always superior to the fixed-model predictors particularly in the non-stationary environment. The framework is conditioned to contextual embeddings, which means that it adjusts smoothly to varying mobility patterns and traffic distributions. This flexibility will make sure that the prediction error is not too large, and thus, the beam can be updated reliably with lower frequency of feedback. Table 5 shows the normalized prediction error of CSI prediction among the various forecasting methods.

Table 5. Normalized CSI prediction error

Method	Static Channel	Dynamic Channel
Linear Predictor	0.21	0.38
LSTM Predictor	0.14	0.26
Proposed Hypernetwork	0.08	0.15

Last but not least, end-to-end performance comparison summarizes all the advantages of the offered framework. In trade-offs of spectral efficiency, energy, latency, overhead, the framework always provides a better trade-off as compared to baseline schemes. These advantages are not lone implementations but a combination of a short-coordinated design that the predictive intelligence, the topology consciousness, and the economy of power support the others. The findings demonstrate that the framework does not only optimize the metrics of individual products but a paradigm shift in the approach to beam management within the massive MIMO systems.

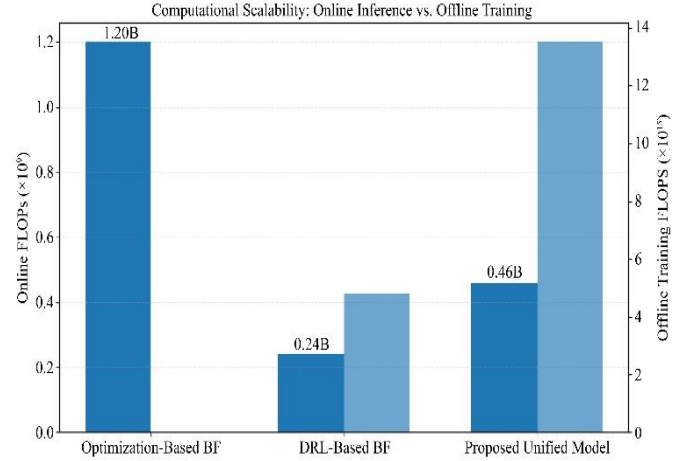


Fig. 5 Computational scalability comparison

Figure 5 shows a comparison between the computational complexity (direct FLOP counts) of offline training and online beam adaptation. Optimization-based beamforming has the highest online complexity of 1.20 billion FLOPs per adaptation iteration and the complexity of $O(K^3)$. It is found that this DRL-based method needs 0.24 billion online FLOPs and 4.80×10^{15} offline training FLOPs. Due to the multi-module design, the number of FLOPs of the proposed unified model is 0.46 G for online processing and 1.35×10^{16} for training. Therefore, the proposed framework is able to achieve the following: reduce online iteration requirements during run-time, training and inference complexity increases during run-time as compared with single-model DRL. A holistic comparison between key performance indicators is presented in Table 6.

Table 6. Overall performance comparison

Metric	Conventional Hybrid BF	DRL-Based BF	Proposed Framework
Spectral Efficiency	Medium	High	Very High
Energy Efficiency	Low	Medium	High
CSI Overhead	High	Medium	Low
Scalability	Limited	Good	Excellent

This work has shown through results and discussion that the suggested unified adaptive beam management framework is not only providing consistent considerable gains but also gains across all the dimensions of massive MIMO performance that are considered relevant in such a study. Combining the operations of prediction, learning, topology awareness, and energy efficiency, the framework offers the sustainable and future-ready framework that will be able to sustain the high requirements of 5G evolution and upcoming 6G networks.

Table 7. Ablation study of framework components

Configuration	Spectral Efficiency (bps/Hz)	Power Consumption (W)	CSI Overhead (%)	Beam Adaptation Latency (ms)	Mobility Variance (bps/Hz)
DRL Only	16.8	430	100	2.8	11.6
DRL + GNN	20.7	395	82	2.4	7.8
DRL + GNN + Hyper-network	23.6	360	61	1.9	4.6

In Table 7, the ablation results show a gradual contribution of each part of the framework. The result of DRL alone is 16.8 bps/Hz with 430 W of power consumption, 100% CSI overhead, 2.8 ms latency and 11.6 bps/Hz mobility variance. With the inclusion of GNN, spectral efficiency of 20.7 bps/Hz is achieved while power reduces to 395 W, CSI overhead to 82%, latency to 2.4 ms, and variance of 7.8 bps/Hz. The Total DRL+GNN+Hypernetwork setup results in 23.6 bps/Hz, 360 W, 61% overhead, 1.9 ms latency, and 4.6 bps/Hz variance, which shows complementary gains through all the components.

5. Conclusion

This work has introduced a coherent and energy-effective beam management system that aims to advocate the root issues of Massive MIMO systems in the current 5G networks and the future 6G networks. Though Massive MIMO provides an impressive spectral efficiency and network capacity improvement, it is limited practically by a high complexity of its computations, too large overhead of CSI acquisition and increasing power consumption in dynamic and dense settings. The predicted framework addresses these shortcomings as it closely combines hybrid analog-digital beamforming with multi-layer learning-driven intelligence that allows intelligence-driven, predictive, and sustainable beamforming adjustment.

One of the key contributions of this work is that there is a combined approach rather than a separation to the beam adaptation and CSI management as a single optimization problem. Through deep reinforcement learning, the system can conduct real-time beam optimization that considers user mobility, changes in interference as well as traffic dynamic and optimize long term performance goals. Turn to graph-aware learning further extends the adaptability aspect by incorporating the network topology and spatial relationship in the decision making process that enables the framework to respond more to the dense user deployments and the sophisticated interference patterns. Neuro-symbolic policy optimization has brought an additional dimension of distinguish ability and consistency to the learning process. The proposed approach, by jointly combining the predictability and more energy-conscious control behavior based on data-driven learning and symbolic constraints and domain knowledge, overcomes one of the limitations of the purely black-box learning methods, namely predictability.

Spatio-temporal hyper network-based CSI forecasting, in parallel, allows proactive beam management, i.e., predicting the channel conditions in the future, which requires little to no frequent feedback of CSI measurements to the system and avoids the effects of feedback latency.

The predictive feature is critical in reducing signaling overheads with a strong link quality. The effectiveness of the proposed framework is proved by simulation outcomes that show significant in terms of spectral efficiency and power savings and computational scalability, in comparison with the conventional and non-predictive learning-based methods. What is worth noting in relation to these gains is the importance of incorporating predictive intelligence and energy consciousness in beam management especially in the high mobility and dynamically evolving network environment. Significantly, the framework can be used alongside applicable hybrid beamforming implementations, which supports its usefulness in a real-life context.

To sum up, the suggested adaptive beam management system is an important step towards intelligent, scalable and sustainable Massive MIMO networks. This work unites predictive learning, structured intelligence and energy efficient design in one architecture, which are the main goals of the future wireless systems. The given method suggests a versatile basis of the further evolution of research and development and opens the access into the new sphere of more autonomous, more robust, more energy-aware beam management solutions in the wireless communications of future generations.

Conflicts of Interest

We declare that there is no conflict of interest regarding the publication of this paper.

Funding Statement

The research and publication of the article was not funded by financially supporting bodies.

Acknowledgments

We gratefully acknowledge the support and guidance provided by our mentors, colleagues, and institution. Their valuable contributions were essential to the successful completion of this work.

References

- [1] Keunyoung Kim et al., "Beamforming and Power Optimization for User Fairness in Cell-Free MIMO Systems," *IEEE Access*, vol. 11, pp. 51032-51046, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [2] Maksym Girnyk, Henrik Jidhage, and Sebastian Faxér, "Broad Beamforming Technology in 5G Massive MIMO," *Ericsson Technology Review*, vol. 2023, no. 10, pp. 2-6, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [3] Ali Hosseinalipour Jazi, S. Mohammad Razavizadeh, and Tommy Svensson, "Integrated Access and Backhaul (IAB) in Cell-Free Massive MIMO Systems," *IEEE Access*, vol. 11, pp. 71658-71667, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [4] Boyu Ning et al., "Beamforming Technologies for Ultra-Massive MIMO in Terahertz Communications," *IEEE Open Journal of the Communications Society*, vol. 4, pp. 614-658, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [5] Panagiotis K. Gkonis, "A Survey on Machine Learning Techniques for Massive MIMO Configurations: Application Areas, Performance Limitations and Future Challenges," *IEEE Access*, vol. 11, pp. 67-88, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [6] Hamed Hojatian et al., "Learning Energy-Efficient Transmitter Configurations for Massive MIMO Beamforming," *IEEE Transactions on Machine Learning in Communications and Networking*, vol. 2, pp. 939-955, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [7] Marwa Abdelfatah, Abdelhalim Zekry, and Shaimaa ElSayed, "User Selection Methods for Overcoming Growing Number of Served Users in Massive MIMO Systems," *IEEE Access*, vol. 11, pp. 59981-59994, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [8] Israa Khaled et al., "Angle-Domain Hybrid Beamforming-Based mmWave Massive MIMO-NOMA Systems," *IEEE Open Journal of the Communications Society*, vol. 4, pp. 684-699, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [9] Kengo Ando, Koji Ishibashi, and Giuseppe Thadeu Freitas de Abreu, "Robust Tensor Decomposition for Heterogeneous Beamforming under Imperfect Channel State Information," *IEEE Open Journal of Signal Processing*, vol. 4, pp. 89-98, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [10] Rafid Umayer Murshed et al., "A CNN-LSTM-Based Fusion Separation Deep Neural Network for 6G Ultra-Massive MIMO Hybrid Beamforming," *IEEE Access*, vol. 11, pp. 38614-38630, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [11] Mobeen Mahmood et al., "Achieving Capacity Gains in Practical Full-Duplex Massive MIMO Systems: A Multi-Objective Optimization Approach Using Hybrid Beamforming," *IEEE Open Journal of the Communications Society*, vol. 5, pp. 2268-2286, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [12] Paweł Bienkowski et al., "Simplified Methodology of Electromagnetic Field Measurements in the Vicinity of 5G Massive MIMO Base Station for Environmental Exposure Assessment," *IEEE Access*, vol. 12, pp. 8071-8080, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [13] Wilson De Souza Junior et al., "Manifold-Based Optimizations for RIS-Aided Massive MIMO Systems," *IEEE Open Journal of the Communications Society*, vol. 5, pp. 7913-7940, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [14] Spandan Bisoyi et al., "Outdoor Massive MIMO Testbed with Directional Beams: Design, Implementation, and Validation," *IEEE Access*, vol. 13, pp. 22230-22242, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [15] Mohsen Hossienzadeh, Hassan Aghaeinia, and Mohammad Kazemi, "Deep Learning Based Interference Exploitation in 1-Bit Massive MIMO Precoding," *IEEE Access*, vol. 11, pp. 17096-17103, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [16] Arselan Ashraf et al., "Advancements and Challenges in Scalable Modular Antenna Arrays for 5G Massive MIMO Networks," *IEEE Access*, vol. 12, pp. 57895-57916, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [17] Iqra Farhat, Umar Rashid, and Omer Waqar, "Enhanced Fronthaul Capacity in CRANs: Sum-Rate Maximization via Joint Optimal Design of STAR-RIS, Massive MIMO and Data Compression," *IEEE Open Journal of Vehicular Technology*, vol. 6, pp. 202-215, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [18] Joarder Jafor Sadique, Imtiaz Nasim, and Ahmed S. Ibrahim, "Covariance Shaping over Riemannian Manifolds for Massive MIMO Communication," *IEEE Access*, vol. 11, pp. 142874-142883, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [19] Nura Abdalrhman Alhaj et al., "Integration of Hybrid Networks, AI, Ultra Massive-MIMO, THz Frequency, and FBMC Modulation toward 6G Requirements: A Review," *IEEE Access*, vol. 12, pp. 483-513, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [20] Xuan-Toan Dang, Hieu V. Nguyen, and Oh-Soon Shin, "Optimization of IRS-NOMA-Assisted Cell-Free Massive MIMO Systems Using Deep Reinforcement Learning," *IEEE Access*, vol. 11, pp. 94402-94414, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [21] Aymen Ktari, and Ghaya Rekaya, "Neural Networks for Multi User Beam Management in mmWave Massive MIMO," *2024 IEEE Middle East Conference on Communications and Networking (MECOM)*, Abu Dhabi, United Arab Emirates, pp. 94-99, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [22] Yunke Mo, Fangfang Fan, and Xinyi Zhao, "A Compact Wide-Angle Scanning Antenna Array for U6G Massive MIMO Base Station," *2025 IEEE MTT-S International Wireless Symposium (IWS)*, Xi'an, China, pp. 1-3, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [23] Zhenhai Zhu, Yuan Wu, and Jiajia Hao, "Research on MIMO Beam Integration Optimization Method Based on PredRNN Prediction and Ant Colony Algorithm," *2024 14th International Symposium on Antennas, Propagation and EM Theory (ISAPE)*, Hefei, China, pp. 1-4, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]

- [24] Yuhong Wang, and Jingyi Peng, "Beam Training for Spatial Non-Stationary XL-MIMO," *2023 3rd International Conference on Intelligent Communications and Computing (ICC)*, Nanchang, China, pp. 228-231, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [25] Margaux Pellet et al., "Multibeam Phased Arrays Exploiting Frequency Dispersion for Massive MIMO Satellite Communications," *2024 18th European Conference on Antennas and Propagation (EuCAP)*, Glasgow, United Kingdom, pp. 1-5, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [26] Zhirong Zhang, "Massive MIMO Technology: A Key Advancement in Shaping Communication Networks for the 5G/5G+ Era," *2024 International Wireless Communications and Mobile Computing (IWCMC)*, Ayia Napa, Cyprus, pp. 274-278, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [27] Yuki Sasaki, Kabuto Arai, and Kazuki Maruta, "QRD-based Precoding Design for Multiuser Massive MIMO Null-Space Expansion," *IEICE Communications Express*, vol. 13, no. 12, pp. 509-512, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [28] Yunwu Wang et al., "Energy-Efficient and QoS-Guaranteed 3-D Beam Mapping for Massive MIMO System Under Tidal Traffic Loads," *IEEE Internet of Things Journal*, vol. 11, no. 21, pp. 35023-35035, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [29] Amar D. Chaudhari, and Soumava Mukherjee, "Exploiting the Viability of Antenna Arrays for Multi-Band FR2 Base-Station Massive MIMO Systems," *2024 16th International Conference on COMMunication Systems & NETworkS (COMSNETS)*, Bengaluru, India, pp. 1143-1147, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [30] Wassim Ben Chikha et al., "Radio Environment Map based Inter-Cell Interference Coordination for Massive-MIMO Systems," *IEEE Transactions on Mobile Computing*, vol. 23, no. 1, pp. 785-796, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]