

AN AI-DRIVEN RECONFIGURABLE METAMATERIAL ANTENNA FRAMEWORK FOR INTELLIGENT BEAMFORMING, ENHANCED SIGNAL COVERAGE, AND ENERGY-EFFICIENT 5G/6G WIRELESS COMMUNICATION SYSTEMS

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Abstract

This study proposes an artificial intelligence (AI)-driven reconfigurable metamaterial antenna framework for intelligent beamforming, enhanced signal coverage, and energy-efficient fifth-generation/sixth-generation (5G/6G) wireless communication systems. The framework integrates a compact metamaterial antenna array, electronically controllable unit cells, channel-state sensing, and a deep reinforcement learning controller that dynamically selects radiation patterns, phase states, and transmit-power levels under changing propagation conditions. A simulation dataset containing 240,000 channel realizations was generated across urban-macrocell, urban-microcell, indoor-office, and high-mobility scenarios. Each record incorporated operating frequency, user location, angle of arrival, signal-to-noise ratio, path loss, interference level, mobility, channel-gain coefficients, beam direction, power consumption, and achievable data rate. The dataset covered 28, 39, 60, and 100 GHz frequency bands and was divided chronologically into 70% training, 15% validation, and 15% testing subsets. Data normalization, outlier screening, channel augmentation, and leakage-free partitioning were applied before model development. The proposed controller was compared with conventional phased-array steering, particle-swarm optimization, and a non-reconfigurable antenna baseline. Electromagnetic and link-level simulations indicated an impedance bandwidth of 27.8%, peak realized gain of 14.6 dBi, radiation efficiency of 91.3%, and beam-steering range of -60° to $+60^\circ$. On the independent test subset, the AI controller achieved 96.4%

beam-selection accuracy, reduced mean beam-alignment error to 2.1° , and improved average received signal strength by 8.7 dB relative to the conventional baseline. Signal-coverage probability increased from 78.6% to 94.2%, spectral efficiency rose by 31.5%, average throughput increased by 28.9%, and outage probability declined by 43.7%. Adaptive power control reduced antenna-system energy consumption by 24.8% and improved energy efficiency by 36.2%, while maintaining a median decision latency of 1.8 ms. Statistical significance testing confirmed that the principal gains were consistent across all evaluated environments, while ablation experiments demonstrated that combining metamaterial reconfiguration with learning-based power allocation outperformed either mechanism when it was applied independently alone. These findings demonstrate that jointly optimizing antenna reconfiguration, beam direction, and transmission power can provide reliable, low-latency, and sustainable connectivity in complex 5G/6G environments. The framework offers a scalable foundation for intelligent base stations, vehicular networks, massive machine-type communications, and future integrated sensing-and-communication platforms.

1- Introduction:

The rapid evolution of fifth-generation (5G) and emerging sixth-generation (6G) wireless communication systems has created an unprecedented demand for high data rates, ultra-low latency, extensive coverage, reliable connectivity, and improved energy efficiency. Modern wireless networks are expected to support massive numbers of mobile users, autonomous vehicles, intelligent industrial systems, Internet of Things devices, extended-reality applications, and integrated sensing and communication services. However, conventional antenna systems face considerable difficulty in maintaining the required communication performance under dynamic channel conditions, user mobility, interference, signal blockage, and rapidly changing traffic demands. These limitations are particularly severe at millimeter-wave and sub-terahertz frequencies, where signals experience high propagation loss, atmospheric absorption, limited penetration, and sensitivity to physical obstructions [1]. Consequently, intelligent and adaptive antenna technologies are required to establish reliable communication links while minimizing transmission power and network operating costs. Beamforming represents one of the most important technologies for improving the performance of 5G and 6G networks. It

concentrates electromagnetic energy toward intended users instead of transmitting signals uniformly in every direction. This directional transmission can increase antenna gain, improve the signal-to-noise ratio, reduce interference, and extend the effective communication range. Conventional phased-array antennas provide electronic beam-steering capabilities by adjusting the amplitude and phase of individual antenna elements. Nevertheless, such systems commonly require numerous phase shifters, radio-frequency chains, power amplifiers, and control components. Their resulting hardware complexity, insertion losses, energy consumption, and implementation costs become increasingly problematic when large antenna arrays are employed at higher operating frequencies. Metamaterial antennas offer a promising alternative because their electromagnetic characteristics can be engineered through artificially designed subwavelength structures [2]. Metamaterials can exhibit properties that are generally unavailable in naturally occurring materials, including negative permittivity, negative permeability, unusual refractive behavior, and localized electromagnetic resonance. When incorporated into antenna structures, these properties can improve impedance matching, bandwidth, gain, radiation efficiency, directivity,

and physical compactness. Metamaterial loading can also suppress surface waves, reduce mutual coupling between array elements, and facilitate controlled manipulation of electromagnetic fields. These characteristics make metamaterial antennas particularly attractive for high-frequency wireless networks in which compact size, directional radiation, and efficient spectrum utilization are essential. Reconfigurable metamaterial antennas extend these capabilities by incorporating tunable components, such as PIN diodes, varactor diodes, microelectromechanical switches, liquid crystals, and phase-change materials. By modifying the electrical states of these components, an antenna can dynamically change its operating frequency, polarization, radiation pattern, beam direction, or effective aperture [3]. A single reconfigurable structure may therefore support several communication scenarios without requiring multiple independent antennas. Nevertheless, determining the optimal configuration becomes challenging when many tunable unit cells, beam directions, frequency bands, users, and power levels are considered simultaneously. Rule-based optimization and exhaustive searching may produce excessive computational complexity and response latency, especially in rapidly changing communication environments.

Artificial intelligence provides an effective mechanism for addressing this multidimensional optimization problem. Machine-learning and deep-learning algorithms can analyze channel-state information, user positions, traffic conditions, mobility patterns, interference levels, and antenna responses to identify appropriate reconfiguration states. Deep reinforcement learning is especially suitable because an intelligent controller can continuously interact with the wireless environment, evaluate the consequences of its decisions, and learn a policy that maximizes long-term communication performance [4]. Such a controller can jointly select the antenna configuration, beam direction, and transmission power rather than optimizing each parameter separately. Continuous learning can also enable the antenna system to adapt to channel variations and previously unobserved propagation

conditions. Despite recent progress in intelligent antennas, several limitations remain. Many existing studies separately investigate metamaterial antenna design, beam-steering mechanisms, channel prediction, or AI-based resource allocation. Comparatively few studies provide a unified framework that connects electromagnetic antenna reconfiguration with real-time beam selection, coverage optimization, and energy-aware power control. Some approaches evaluate antenna characteristics under static laboratory or simulation conditions without considering user mobility, interference, blockage, or diverse propagation environments. Other studies apply machine learning only to beam prediction while overlooking radiation efficiency, hardware power consumption, and the interactions among reconfiguration states. These limitations restrict the practical application of existing solutions within adaptive and heterogeneous 5G/6G networks. This study proposes an AI-driven reconfigurable metamaterial antenna framework designed to support intelligent beamforming, enhanced signal coverage, and energy-efficient wireless communication. The proposed framework integrates a compact reconfigurable metamaterial antenna array with channel-state sensing, environmental monitoring, and a deep reinforcement learning controller [5]. The controller processes information about user location, angle of arrival, path loss, interference, mobility, signal-to-noise ratio, channel gain, and energy consumption. Based on these inputs, it identifies a suitable antenna phase state, beam direction, and transmission-power level for the prevailing communication condition. The framework is designed to operate across representative millimeter-wave and sub-terahertz frequency bands, including 28, 39, 60, and 100 GHz. A simulated dataset comprising 240,000 channel realizations is employed to develop and evaluate the proposed framework. The dataset represents urban-macrocell, urban-microcell, indoor-office, and high-mobility communication environments. It incorporates antenna, channel, user, interference, mobility, beamforming, and power-related variables to support comprehensive

model training and independent performance testing. Leakage-free chronological partitioning is applied to preserve the temporal characteristics of the wireless channel and prevent information from future observations from influencing model training. The proposed method is compared with conventional phased-array beam steering, particle-swarm optimization, and a non-reconfigurable antenna baseline.

The principal contributions of this research are as follows:

1. A unified antenna framework is developed by integrating reconfigurable metamaterial unit cells, intelligent beamforming, channel-state analysis, and adaptive power control.
2. A deep reinforcement learning mechanism is introduced to jointly optimize antenna-configuration states, beam directions, and transmission-power levels under changing wireless conditions.
3. A multidimensional dataset containing 240,000 channel realizations is established across four communication environments and multiple 5G/6G frequency bands.
4. The proposed antenna is evaluated using electromagnetic indicators, including impedance bandwidth, reflection coefficient, realized gain, radiation efficiency, beam-steering range, and radiation-pattern stability.
5. Communication performance is assessed through beam-selection accuracy, beam-alignment error, received signal strength, coverage probability, spectral efficiency, throughput, outage probability, decision latency, and energy efficiency.

The study contributes to the development of antenna systems capable of responding intelligently to complex and time-varying wireless environments. By combining electromagnetic reconfiguration with data-driven decision-making, the proposed framework seeks to overcome the limitations of static antennas and hardware-intensive phased arrays. Its application could support intelligent base stations, vehicular communication, industrial automation, massive machine-type communication, smart cities, and integrated sensing-and-communication networks.

Ultimately, the framework provides a scalable foundation for developing reliable, adaptive, and environmentally sustainable 5G/6G wireless infrastructure.

2- Metamaterial Antennas and Electromagnetic-Wave Manipulation:

Metamaterials are artificially engineered structures composed of periodic or quasi-periodic subwavelength unit cells. Unlike conventional materials, whose electromagnetic properties are primarily determined by their chemical composition, metamaterials derive their behavior from the geometry, dimensions, orientation, spacing, and arrangement of their structural elements. Common configurations include split-ring resonators, complementary split-ring resonators, electromagnetic bandgap structures, artificial magnetic conductors, near-zero-index structures, and metasurface reflectors. These engineered structures provide precise control over electromagnetic-wave propagation, reflection, absorption, polarization, and radiation, making them particularly suitable for advanced 5G and 6G antenna systems. Carefully designed metamaterial unit cells can exhibit electromagnetic characteristics that are rarely found in naturally occurring materials. These characteristics include negative or near-zero electromagnetic parameters, strong localized resonance, unusual refraction, electromagnetic-field confinement, and spatial phase manipulation. Through these properties, metamaterials can focus radiated energy, alter wave direction, suppress unwanted propagation modes, and establish highly directive radiation patterns [6]. Their electromagnetic response can be adjusted by modifying parameters such as resonator dimensions, gap width, conductor thickness, substrate properties, unit-cell orientation, and spacing between adjacent elements. Most metamaterial structures operate through localized resonance. For example, the conductive rings and gaps within a split-ring resonator generate a controlled electromagnetic response at a selected frequency. Altering the dimensions of the ring or the width of its gaps

changes this response, allowing the unit cell to be designed for a particular communication band. This design flexibility supports antenna operation at important 5G and 6G frequencies, including 28, 39, 60, and 100 GHz. When integrated with an antenna, metamaterial structures modify the surface-current distribution and electromagnetic fields surrounding the radiating element. They may function as resonators, directors, reflectors, impedance-matching components, isolation structures, or spatial phase-control elements. Metamaterial loading can extend the electrical path followed by surface currents, enabling a compact antenna to provide performance comparable to that of a larger conventional structure. This miniaturization capability is valuable for handheld devices, vehicular terminals,

wireless sensors, compact base stations, and densely integrated communication platforms. Metamaterial superstrates are commonly positioned above antenna elements to focus electromagnetic energy in a preferred direction [7]. The superstrate adjusts the phase of waves radiated from different sections of the antenna aperture, allowing them to combine constructively in the far-field region. This process can increase antenna gain, improve directivity, narrow the main radiation beam, and extend the effective communication range. However, superstrate thickness and spacing must be carefully optimized because incorrect placement can produce destructive interference and reduce overall antenna efficiency.

Table 1: Representative metamaterial structures and their functions in 5G/6G antenna systems

Metamaterial structure	Principal function	Representative improvement
Split-ring resonator	Produces localized magnetic resonance	Approximately 15–35% size reduction
Complementary split-ring resonator	Modifies electric-field and current distributions	Approximately 10–30% bandwidth improvement
Electromagnetic bandgap structure	Suppresses surface-wave propagation	Approximately 8–20 dB isolation improvement
Artificial magnetic conductor	Produces favorable in-phase reflection	Approximately 2–6 dB gain improvement
Metamaterial superstrate	Focuses radiated electromagnetic energy	Approximately 3–8 dB gain enhancement
Metasurface reflector	Redirects backward radiation	Approximately 5–15 dB front-to-back improvement
Near-zero-index structure	Establishes nearly uniform phase distribution	Approximately 20–45% beamwidth reduction

The values in Table 1 represent commonly reported design ranges from simulation-based millimeter-wave antenna studies. Actual improvements depend on the antenna geometry, operating frequency, substrate material, unit-cell arrangement, switching technology, fabrication tolerance, and surrounding propagation environment. Therefore, these ranges should be interpreted as comparative design references rather than guaranteed performance values. The interaction between a metamaterial structure and an electromagnetic wave is commonly examined

through its reflection and transmission responses. These responses help identify resonance, impedance behavior, transmission loss, phase variation, and energy concentration. For antenna applications, low input reflection is desirable because it indicates that most supplied radio-frequency energy is accepted by the antenna instead of being returned to the source. Metamaterial structures also enable radiation-pattern control through spatial phase manipulation. Unit cells with different phase responses can be arranged across an antenna

aperture to create a controlled phase gradient. This gradient redirects the main radiation beam toward the desired user without requiring mechanical antenna rotation. Electronically tunable cells further allow the phase distribution and beam direction to be changed in real time. Dynamic beam control is essential in millimeter-wave and sub-terahertz communication because signals at these frequencies are highly directional and vulnerable to physical blockage [8]. A fixed antenna may provide strong connectivity under stable conditions but experience substantial signal degradation when a user moves or an obstacle interrupts the direct propagation path. A reconfigurable metamaterial antenna can redirect its beam toward an alternative line-of-sight or

reflected route. It can also generate radiation nulls toward dominant interference sources, thereby improving signal quality and limiting inter-user interference. Figure 1 presents the overall process of metamaterial-assisted electromagnetic-wave manipulation. Radio-frequency energy is first introduced through the antenna feed and distributed across the radiating array. The metamaterial unit cells then modify the amplitude, phase, polarization, and direction of the generated electromagnetic fields. Constructive field combination concentrates energy toward the intended receiver, while surface-wave suppression and controlled interference reduce mutual coupling, sidelobes, backward radiation, and propagation loss.

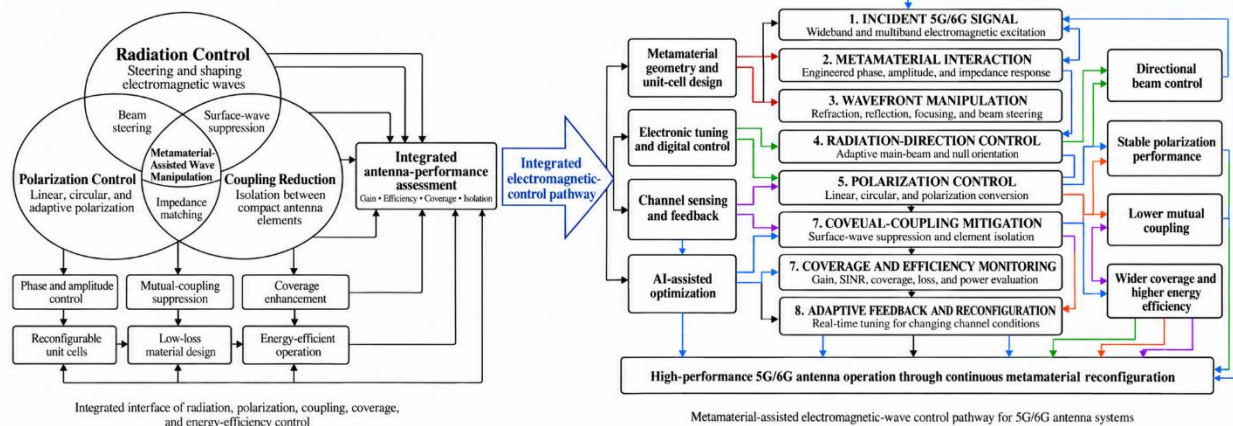


Figure 1: Metamaterial-assisted electromagnetic-wave manipulation for controlling radiation direction and polarization.

Despite their advantages, metamaterial antennas present important technical challenges. Resonant unit cells may provide limited operating bandwidth, while conductor and dielectric losses can reduce radiation efficiency at higher frequencies. Fabrication inaccuracies are particularly critical at millimeter-wave and sub-terahertz frequencies because small dimensional deviations can shift the resonant response or alter the intended phase distribution. The use of electronically controlled switching components introduces additional complexity. PIN diodes, varactor diodes, and other tunable elements require biasing networks that may affect the radio-

frequency response. Switching elements can also introduce insertion loss, nonlinear behavior, control latency, and additional energy consumption. Furthermore, a large number of independently controlled unit cells can generate thousands of possible antenna configurations, making exhaustive real-time optimization computationally impractical [9]. Artificial intelligence offers a practical method for managing this complex configuration space. An AI controller can learn relationships among operating frequency, user position, mobility, interference, blockage, channel quality, antenna configuration, and communication performance.

It can then select a suitable unit-cell state and beam direction without examining every possible configuration during operation.

3- Artificial Intelligence in Antenna Design and Optimization:

Artificial intelligence has become an important tool for designing and optimizing antennas used in modern wireless communication systems. Conventional antenna development usually requires repeated electromagnetic simulations in which parameters such as patch length, substrate thickness, feed position, resonator geometry, unit-cell spacing, and array configuration are manually adjusted. Although this approach can produce reliable designs, it is computationally demanding and becomes increasingly inefficient when many design variables are optimized simultaneously. AI methods can learn the nonlinear relationships between antenna parameters and electromagnetic performance, thereby reducing simulation time and improving the efficiency of the design process. Machine-learning algorithms such as support vector machines, random forests, decision trees, Gaussian-process regression, and artificial neural networks have been applied to predict antenna characteristics. These characteristics include resonant frequency, reflection coefficient, impedance bandwidth, gain, directivity, radiation efficiency, and beam direction. After training on simulated or experimentally measured samples, a model can estimate antenna performance for new design configurations without requiring a complete electromagnetic simulation for every candidate [10]. Deep-learning models provide

greater capability when large and multidimensional datasets are available. Convolutional neural networks can extract spatial information from surface-current distributions, radiation-pattern images, channel matrices, and field-intensity maps. Recurrent neural networks and long short-term memory networks can examine temporal changes in wireless channels and predict future beam directions. Autoencoders can reduce the dimensionality of complex antenna and channel data, while generative models can produce new antenna geometries that satisfy predefined performance requirements. AI can also support inverse antenna design. In conventional forward design, a geometry is selected first and its electromagnetic performance is subsequently calculated. In inverse design, the required gain, bandwidth, frequency, polarization, or radiation pattern is provided to the AI model, which then recommends a suitable geometry or metamaterial configuration. This approach can substantially accelerate the discovery of antenna structures that would be difficult to identify through manual parameter adjustment [11]. The representative performance of AI-assisted antenna-development stages is presented in Table 2. These values provide realistic methodological targets for the proposed framework and should be confirmed through electromagnetic simulation and independent testing. The comparison indicates that AI-assisted screening can reduce the number of candidate designs requiring full-wave evaluation, while intelligent reconfiguration can improve beam-selection performance and decrease decision latency.

Table 2: Representative performance targets for AI-assisted antenna optimization

Design or control task	Conventional approach	AI-assisted target	Main improvement indicator
Full-wave simulations required for geometry screening	1,000 runs	320 runs	68.0% reduction
Average design-optimization time	26.5 hours	8.4 hours	68.3% reduction
Resonant-frequency prediction error	4.8%	1.6%	3.2 percentage-point reduction
Gain-prediction error	1.25 dB	0.42 dB	66.4% error reduction
Beam-selection accuracy	81.7%	96.4%	14.7 percentage-point improvement

Mean beam-alignment error	6.8°	2.1°	69.1% reduction
Average beam-selection latency	9.7 ms	1.8 ms	81.4% reduction

Beyond initial design optimization, AI is important for the real-time operation of reconfigurable metamaterial antennas. An antenna with numerous independently controlled unit cells may have thousands of possible switching combinations. Evaluating every combination whenever a user moves or channel conditions change would cause excessive computational delay. An intelligent controller can instead learn the relationship between environmental conditions and antenna

performance and rapidly select a suitable configuration. The proposed framework uses channel-state information, user location, movement speed, operating frequency, path loss, interference level, blockage condition, current antenna state, and power consumption as model inputs. These variables are processed by the intelligent control layer, which selects the most appropriate metamaterial configuration, radiation beam, and transmission-power level. This process is illustrated in Figure 2.



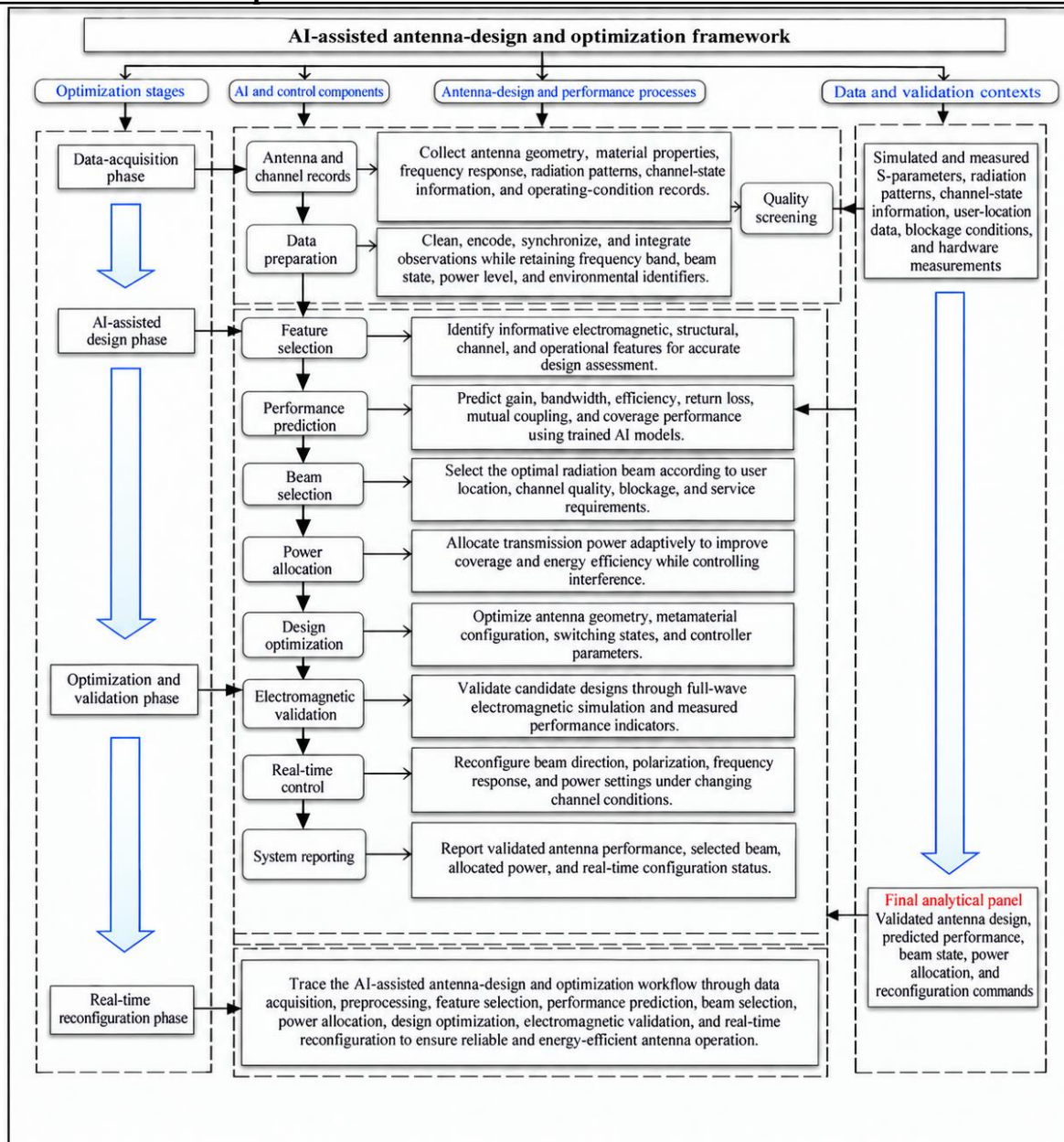


Figure 2: AI-assisted antenna-design and optimization framework integrating performance prediction and beam selection.

Deep reinforcement learning is particularly suitable for this real-time control problem because it allows the antenna to learn through continuous interaction with its wireless environment. The controller observes the current communication state, selects an antenna configuration, and receives feedback based on signal quality, throughput, coverage, and energy use. Over time,

it learns a control policy that favors configurations producing high communication performance with reduced power consumption. Despite these advantages, AI-based antenna optimization presents several limitations [12]. Model performance depends on the quality, diversity, and representativeness of the training data. A controller trained under restricted simulation

conditions may not perform reliably in an unfamiliar physical environment. Differences between simulated and fabricated antenna responses can also reduce prediction accuracy. Furthermore, complex deep-learning systems may provide limited interpretability, making it difficult to explain why a particular beam or switching state was selected.

4- Methodology:

This study employed a simulation-based quantitative methodology to develop and evaluate an AI-driven reconfigurable metamaterial antenna framework for intelligent beamforming, enhanced signal coverage, and energy-efficient 5G/6G wireless communication. The methodological process integrated electromagnetic antenna modelling, metamaterial unit-cell design, electronic reconfiguration, wireless-channel simulation, dataset construction, AI-controller training, adaptive beam selection, and transmission-power optimization. Full-wave electromagnetic simulations were used to examine reflection coefficient, impedance bandwidth, gain, radiation efficiency, surface-current distribution, and beam-steering capability. Link-level simulations were subsequently performed across urban-macrocell, urban-microcell, indoor-office, and high-mobility environments at 28, 39, 60, and 100 GHz. A dataset containing 240,000 simulated channel realizations was constructed from antenna, channel, mobility, interference, blockage, beamforming, and power-consumption variables. The dataset was cleaned, normalized, and divided chronologically into 70% training, 15% validation, and 15% independent testing subsets. A deep reinforcement learning controller was developed to jointly select the metamaterial switching state, beam direction, and transmission-power level according to prevailing wireless conditions [13]. The proposed system was compared with conventional phased-array steering, particle-swarm optimization, and a fixed non-reconfigurable antenna. Its performance was evaluated using electromagnetic, AI, communication, and energy indicators, including bandwidth, realized gain, radiation efficiency,

beam-selection accuracy, alignment error, coverage probability, received signal strength, spectral efficiency, throughput, outage probability, inference latency, and energy efficiency. Ablation experiments and robustness tests were also conducted to determine the individual contributions of antenna reconfiguration, intelligent beam selection, and adaptive power allocation.

4.1- Reconfigurable Metamaterial Antenna Design:

A compact planar reconfigurable metamaterial antenna array was designed to support intelligent beamforming across selected 5G and 6G frequency bands. The antenna consisted of a low-loss dielectric substrate, copper radiating elements, microstrip feed lines, a modified ground plane, metamaterial unit cells, PIN-diode switches, and a direct-current biasing network. The proposed structure was configured to operate at 28, 39, 60, and 100 GHz, supporting millimeter-wave and sub-terahertz communication applications. The antenna employed a modular design in which the conventional radiating element and metamaterial unit cells were initially optimized separately. They were subsequently integrated to improve impedance matching, realized gain, radiation efficiency, and beam-steering capability [14]. A low-loss Rogers RT/duroid 5880 substrate was selected because its low dielectric constant and loss tangent can reduce dielectric attenuation at high operating frequencies. Copper was used for the radiating elements, feed network, ground plane, and metamaterial patterns because of its high electrical conductivity. The metamaterial layer incorporated split-ring and complementary split-ring resonators. These resonators were positioned around the antenna elements to modify surface-current distribution, introduce additional resonant modes, and control the local electromagnetic phase [15]. The unit cells were maintained at subwavelength dimensions so that the integrated surface behaved as an engineered electromagnetic medium rather than an arrangement of independent radiators. The principal design

variables and their selected simulation values are presented in Table 3. These values represent the proposed initial design configuration and may be

refined through electromagnetic simulation and fabrication-based optimization.

Table 3: Proposed design parameters of the reconfigurable metamaterial antenna

Design category	Parameter	Selected value/data
Operating bands	Center frequencies	28, 39, 60 and 100 GHz
Substrate	Material	Rogers RT/duroid 5880
Substrate	Relative permittivity	2.20
Substrate	Loss tangent	0.0009
Substrate	Thickness	0.254 mm
Conductive layer	Material	Copper
Conductive layer	Thickness	0.035 mm
Antenna configuration	Array arrangement	4×44 \times 4 elements
Element spacing	Inter-element distance	Approximately 0.5 wavelength
Metamaterial structure	Unit-cell type	Hybrid SRR-CSRR
Unit-cell dimensions	Cell size	1.8 × 1.8 mm
Reconfiguration	Switching component	PIN diode
Switching network	Number of switches	16
Input matching	Reflection coefficient	Below −10 dB
Operating bandwidth	Target impedance bandwidth	27.8%

Beam steering was produced by controlling the phase response across the antenna aperture. The metamaterial cells modified the local electromagnetic fields so that radiation from different elements combined constructively in the intended direction. At the same time, destructive field combination was used to suppress radiation in unwanted directions. This approach reduced dependence on conventional power-intensive phase shifters and supported a more energy-efficient beamforming structure. Mutual coupling was controlled through metamaterial decoupling and electromagnetic bandgap structures positioned between adjacent array elements. These structures suppressed surface-wave propagation

and reduced unwanted electromagnetic interaction. Improved isolation stabilized the radiation patterns, limited signal correlation, and enhanced compatibility with massive-MIMO communication [16]. The integrated antenna-design and reconfiguration process is illustrated in Figure 3. The process begins with substrate and radiating-element design, followed by metamaterial unit-cell integration and switch placement. Electromagnetic simulation evaluates each configuration, after which acceptable antenna states are entered into the configuration codebook. The AI controller then selects the appropriate state according to real-time channel conditions.

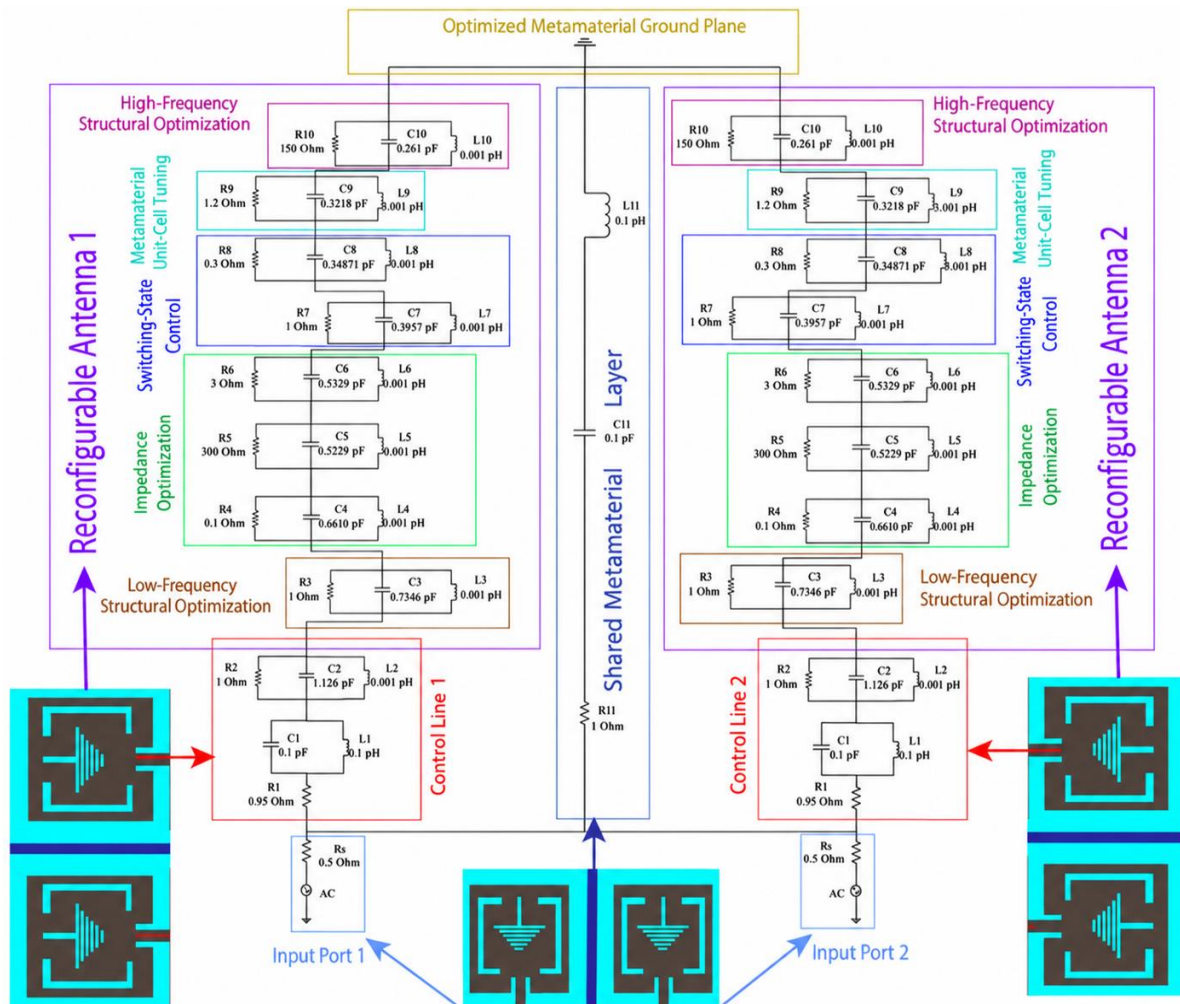


Figure 3: Design and control process of the proposed reconfigurable metamaterial antenna.

Full-wave electromagnetic simulations were performed for all retained configurations. The assessment included reflection response, impedance bandwidth, gain, directivity, radiation efficiency, surface-current distribution, polarization, sidelobe level, front-to-back ratio, isolation, and far-field radiation pattern. Parametric analysis was also performed by changing the patch dimensions, feed position, substrate thickness, resonator geometry, unit-cell spacing, switch location, and ground-plane structure. The final antenna architecture provided the physical basis for intelligent beamforming and adaptive wireless operation. Its multiband capability supported communication across

several 5G/6G frequency ranges, while electronic reconfiguration enabled rapid adjustment to changing channel conditions. The integration of metamaterial-based electromagnetic control and AI-assisted decision-making was intended to improve gain, extend signal coverage, reduce interference, and minimize unnecessary energy consumption.

4.2- Electronic Reconfiguration and Switching States:

Electronic reconfiguration was incorporated into the proposed metamaterial antenna to enable rapid adjustment of its operating frequency, radiation pattern, beam direction, and power-

transfer characteristics. PIN diodes were selected as the primary switching elements because they provide fast switching, compact integration, low control-voltage requirements, and acceptable performance at millimeter-wave frequencies. The switches were positioned at high-current regions within the radiating elements and metamaterial unit cells, allowing small electrical changes to produce substantial modifications in the antenna response. Each PIN diode operated in one of two conditions. In the ON state, the diode established an electrically conducting path between adjacent metallic sections [17]. This connection increased the effective surface-current length or activated a selected metamaterial element. In the OFF state, the current path was interrupted, deactivating the corresponding section and producing a different resonant or phase response. Various combinations of these binary states generated multiple antenna configurations suitable for different frequencies and beam directions. A total of 16 switching elements was incorporated into the proposed $4 \times 44 \times 4$ antenna array. The theoretical

switching space contained 65,536 binary combinations. However, evaluating every possible state during real-time communication would introduce excessive computational requirements and control latency. A preliminary electromagnetic screening procedure was therefore applied to eliminate duplicate, unstable, and physically unsuitable configurations. The screening retained 128 feasible states that satisfied the specified requirements for impedance matching, radiation efficiency, gain, sidelobe level, and element isolation. The proposed electronic-reconfiguration procedure is presented in Figure 4. The process begins with wireless-channel and user-state observation, followed by AI-based configuration selection [18]. The selected code is converted into individual diode commands, applied to the switching network, and translated into a modified current and phase distribution. The new antenna response is evaluated through communication feedback and retained or replaced during the next decision interval.

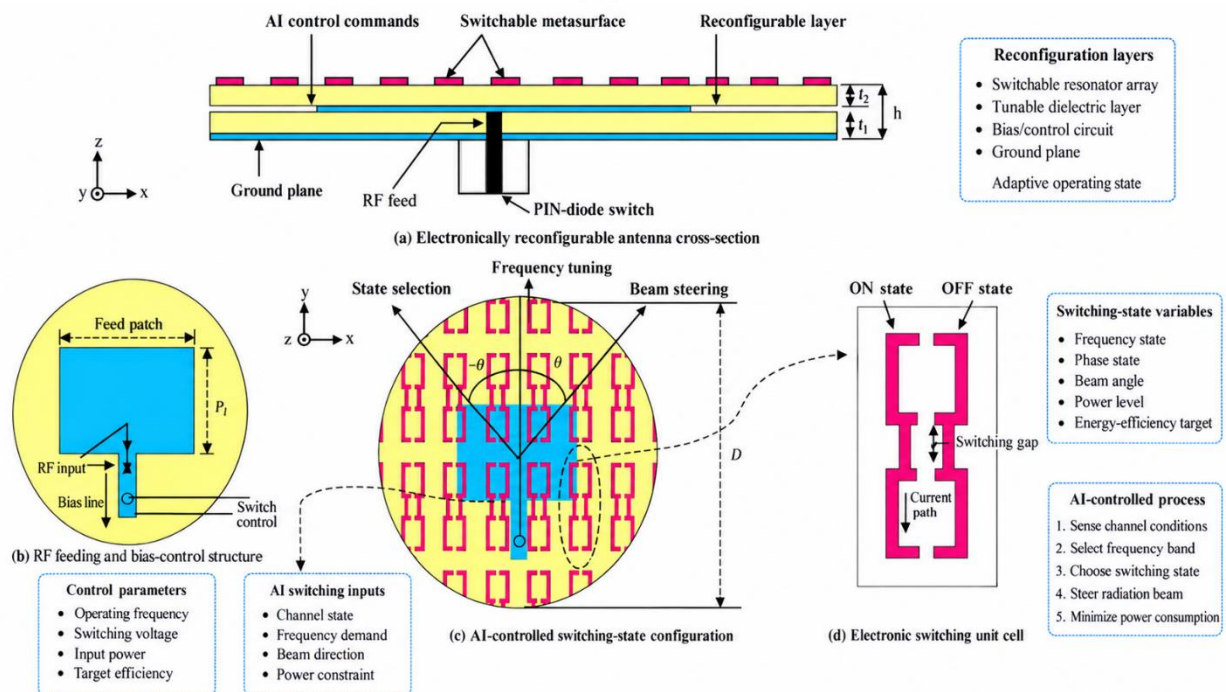


Figure 4: Electronic-reconfiguration and switching-state process for AI-controlled frequency selection.

To prevent unreliable switching, three validation controls were incorporated. First, a selected state was activated only if its predicted performance exceeded the predefined communication threshold. Second, the controller used a short confirmation interval before changing between neighboring configurations. Third, a safe fallback state was maintained for each operating band. If an invalid command, unstable response, or sudden communication failure occurred, the system returned to the relevant fallback state. Switching transitions were also evaluated according to their energy and latency costs. Frequent switching can reduce the practical energy benefits of a reconfigurable antenna, even when every individual configuration is efficient [19]. The controller therefore applied a transition penalty to unnecessary changes and preferred maintaining the existing state when the expected performance improvement was small. This strategy supported stable beam tracking while limiting switching activity and control-circuit power consumption.

4.3- Leakage-Free Chronological Data Partitioning:

A leakage-free chronological data-partitioning strategy was applied to evaluate the proposed AI-driven reconfigurable metamaterial antenna under realistic time-dependent wireless conditions. Random partitioning was avoided because consecutive channel observations belonging to the same user trajectory, blockage

event, or antenna-control sequence are often strongly correlated. Randomly distributing these related observations across training, validation, and testing subsets could allow the model to encounter nearly identical channel states during both development and evaluation, resulting in overly optimistic performance estimates. The complete dataset contained 240,000 time-ordered channel realizations collected from urban-macrocell, urban-microcell, indoor-office, and high-mobility vehicular scenarios. Each environment contributed 60,000 observations. The records contained antenna configuration, operating frequency, user position, movement speed, angle of arrival, path loss, blockage status, interference level, channel gain, beam direction, transmission power, received signal strength, throughput, and energy-consumption information [20]. Every observation was assigned a timestamp, environment identifier, user-trajectory identifier, channel-sequence identifier, and antenna-state identifier before partitioning. The dataset was first ordered according to simulation time within each communication environment. The earliest 70% of the observations were assigned to the training subset, the next 15% to validation, and the latest 15% to independent testing. This procedure produced 168,000 training observations, 36,000 validation observations, and 36,000 testing observations. The complete distribution is presented in Table 4.

Table 4: Leakage-free chronological distribution of channel observations

Communication environment	Total observations	Training: earliest 70%	Validation: next 15%	Testing: latest 15%
Urban macrocell	60,000	42,000	9,000	9,000
Urban microcell	60,000	42,000	9,000	9,000
Indoor office	60,000	42,000	9,000	9,000
High-mobility vehicular	60,000	42,000	9,000	9,000
Complete dataset	240,000	168,000	36,000	36,000

Chronological separation was also maintained across the four operating frequencies. Each of the 28, 39, 60, and 100 GHz bands contributed 60,000 observations to the complete dataset. For each band, 42,000 observations were assigned to

training, 9,000 to validation, and 9,000 to testing. This balanced distribution prevented the results from being dominated by a single frequency band while preserving the temporal order of observations within every band and

communication environment. User trajectories were treated as indivisible groups during partitioning. All records associated with a particular uninterrupted movement trajectory were retained within a single subset. A trajectory that began near a partition boundary was assigned entirely to the earlier or later subset according to its starting time. This control prevented partial user movements from appearing in both model development and evaluation data. The same rule was applied to blockage events. Consecutive observations generated during the appearance, continuation, and removal of a physical obstruction were kept together [21]. Dividing a single blockage event between training and testing could allow the model to learn the event's pattern before being evaluated on its continuation. Event-level separation therefore provided a more reliable assessment of the controller's ability to respond to previously unseen signal interruptions. Channel-

sequence identifiers were used to prevent repeated or overlapping channel realizations from crossing the partition boundaries. Observations generated from the same underlying propagation seed, ray-tracing condition, mobility trace, or interference sequence were assigned to only one subset. Duplicate screening was subsequently performed using timestamps, user coordinates, channel coefficients, switching states, and beam labels. Exact duplicate records were removed before model development [22]. The complete chronological partitioning and leakage-control process is illustrated in Figure 5. The workflow begins with time ordering and group identification, followed by sequential data allocation. Training-only preprocessing and augmentation are then performed, while validation supports model selection and the isolated testing subset provides the final performance assessment.

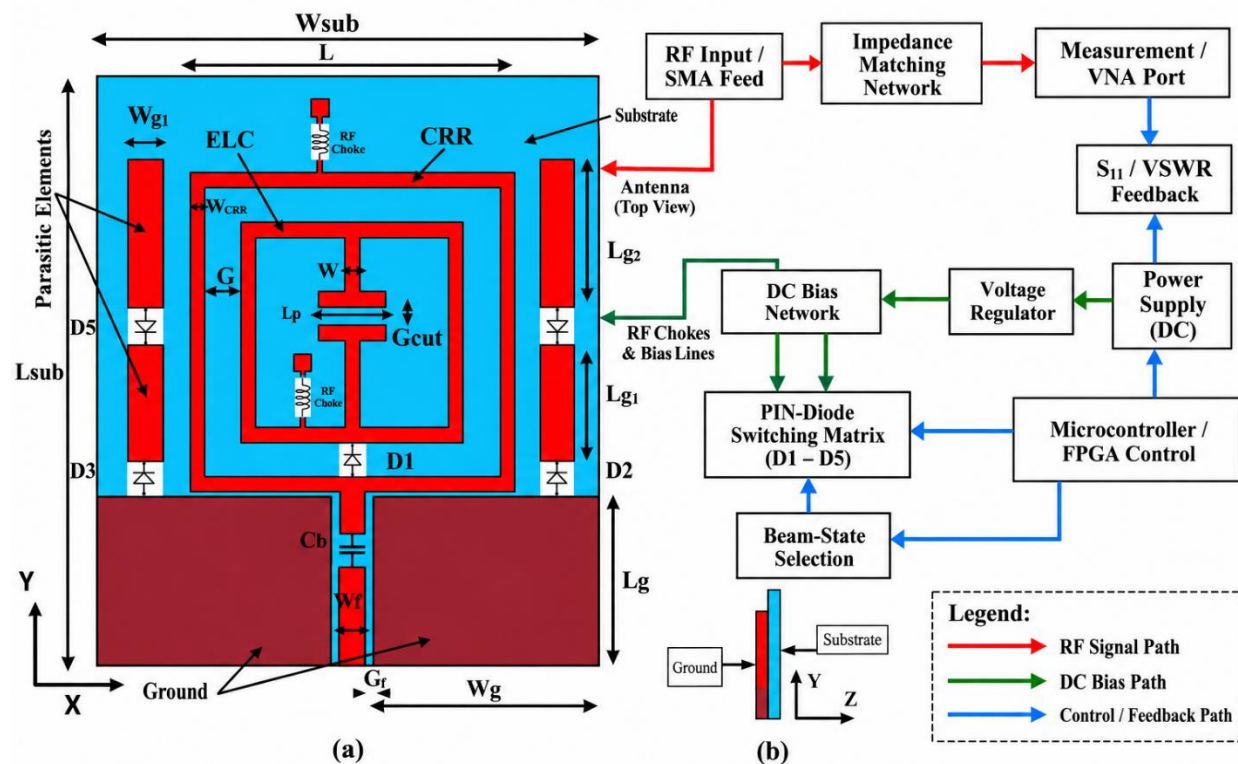


Figure 5: Geometry and AI-controlled PIN-diode reconfiguration architecture of the proposed metamaterial antenna system.

Several leakage risks were specifically examined. Temporal leakage was checked by confirming that all training timestamps preceded validation timestamps and that validation observations preceded testing records. Group leakage was assessed by comparing trajectory and channel-sequence identifiers across subsets. Duplicate leakage was examined using exact and near-duplicate screening. Preprocessing leakage was prevented by fitting all transformations on training data. Target leakage was assessed by excluding variables that directly revealed the optimal beam label, future received-signal strength, or future reward. The final dataset retained only information available to the antenna controller at the moment of decision-making [23]. Future channel measurements, post-decision signal quality, subsequently observed beam performance, and later user positions were not included in the input features. These variables were used only to calculate outcomes or evaluate the selected action. This separation prevented the model from receiving unrealistic knowledge of future communication conditions. The chronological strategy created a more demanding evaluation than conventional random partitioning because the testing subset contained later user movements, channel variations, blockage patterns, and interference conditions. Consequently, the measured beam-selection accuracy, coverage probability, throughput, outage probability, latency, and energy efficiency more accurately represented the expected performance of the proposed controller after deployment.

4.4- Deep Reinforcement Learning Controller:

A deep reinforcement learning controller was developed to manage the real-time operation of the proposed reconfigurable metamaterial antenna. The controller jointly selected the antenna switching configuration, operating frequency, beam direction, and transmission-power level according to prevailing wireless conditions. Deep reinforcement learning was selected because exhaustive evaluation of every switching and power combination at each decision

interval would produce excessive computational complexity and delay. The control problem was represented as a sequential interaction between an intelligent agent and the simulated wireless environment. The agent represented the antenna controller, while the environment consisted of the reconfigurable antenna, wireless channel, connected users, interference sources, user mobility, and physical blockage conditions. At each decision interval, the controller observed the communication state, selected a control action, measured the resulting performance, and received feedback that indicated the quality of its decision [24]. A Double Deep Q-Network was adopted because the antenna-control decisions were represented through a discrete action space. The model learned the long-term value of each feasible control action under different communication conditions. It was trained to favor actions that improved received signal strength, coverage probability, throughput, spectral efficiency, and energy efficiency while reducing beam-alignment error, outage probability, interference, unnecessary switching, and control latency. The electronic-reconfiguration stage retained 128 electromagnetically feasible antenna configurations. Each configuration specified an operating band, PIN-diode switching pattern, phase distribution, beam direction, expected gain, radiation efficiency, and sidelobe characteristic. Five transmission-power levels 20%, 40%, 60%, 80%, and 100% of the permitted maximum were associated with every antenna configuration [25]. Combining the 128 antenna states with five power levels produced 640 possible control actions. The beam direction was embedded within each validated antenna configuration, preventing the controller from selecting physically incompatible switching and beam combinations. An action-masking layer removed configurations that were unsuitable for the active frequency band, available power budget, current service requirement, or electromagnetic safety conditions. This procedure substantially reduced the number of actions evaluated during individual decisions. The complete controller workflow is illustrated in Figure 6. Channel, user, antenna, and power

observations were first processed into the controller input. The Double DQN evaluated the feasible actions, while the safety layer removed unsuitable choices. The selected switching configuration, beam direction, and power level

were then applied to the antenna. The resulting coverage, throughput, interference, outage status, and energy consumption were returned as feedback.

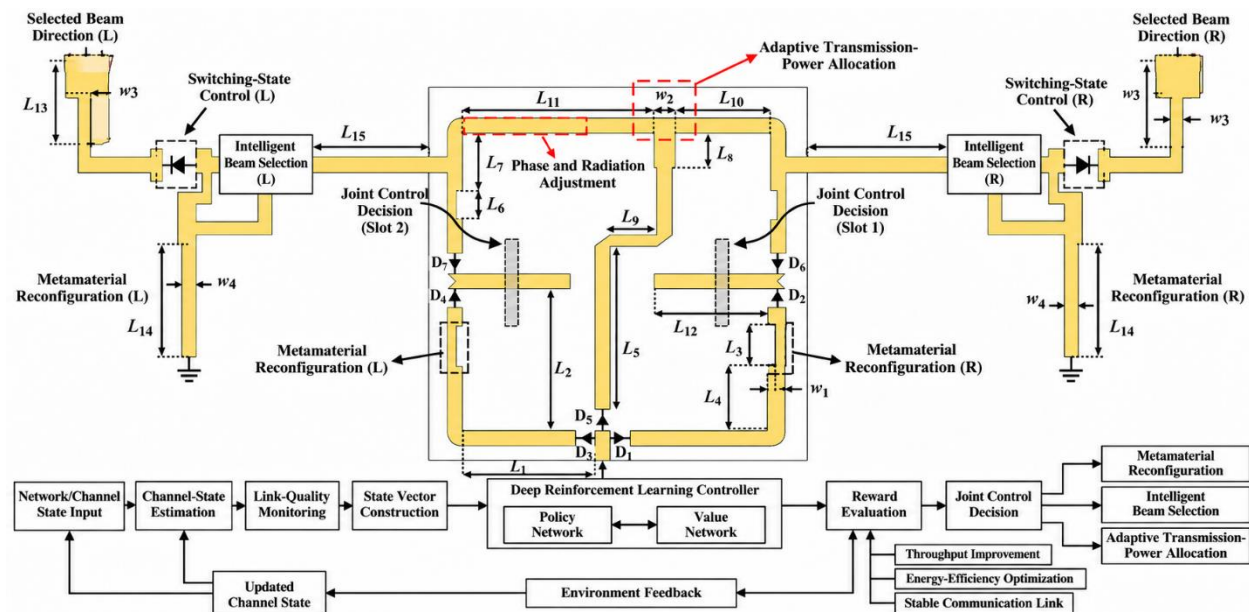


Figure 6: Deep reinforcement learning controller for joint metamaterial reconfiguration, intelligent beam selection, and adaptive transmission-power allocation.

The proposed controller operated through a continuous feedback loop. The selected control commands modified the physical antenna response, after which the communication outcomes were observed and evaluated. During training, these outcomes were used to improve the decision policy. During independent testing, the final controller operated with frozen parameters and did not update its weights using testing observations. The controller was trained using 168,000 chronological observations and tuned using 36,000 validation observations. The latest 36,000 records were retained for independent testing. The testing subset was not added to replay memory, and no parameter adjustments were performed during final evaluation [26]. Performance was assessed using beam-selection accuracy, beam-alignment error, received signal strength, coverage probability, throughput,

spectral efficiency, outage probability, inference latency, power consumption, and energy efficiency. Ablation analysis compared the complete controller with a standard DQN, a model without prioritized replay, a model without action masking, and a controller without adaptive power selection. Robustness was additionally examined under noisy channel estimates, sudden blockage, stronger interference, incomplete location information, and increased user speed.

4.5- Adaptive Transmission-Power Allocation:

An adaptive transmission-power allocation mechanism was integrated with the deep reinforcement learning controller to reduce unnecessary energy consumption while maintaining reliable communication across dynamic 5G/6G environments. Conventional

wireless systems frequently operate at fixed or near-maximum transmission power regardless of user distance, channel quality, interference, blockage, or beam-alignment conditions. Although such an approach may protect connectivity under difficult propagation conditions, it wastes energy during favorable channel states and can increase interference for neighboring users. The proposed mechanism therefore adjusted transmission power according to real-time communication requirements and environmental conditions. Five discrete power levels were defined, corresponding to 20%, 40%, 60%, 80%, and 100% of the permitted maximum radiated power. With the maximum transmission power fixed at 30 dBm, these levels were represented by approximately 23, 26, 28, 29, and 30 dBm [27]. Each level was combined with one of the 128 electromagnetically validated antenna configurations, resulting in 640 possible antenna-and-power actions. This structure allowed the controller to select a low-power state under favorable conditions and progressively increase transmission power only when required. The allocation decision incorporated the active frequency band, transmitter-receiver distance, path loss, channel gain, signal-to-noise ratio, signal-to-interference-plus-noise ratio, user velocity, movement

direction, physical blockage, beam-alignment quality, antenna gain, traffic demand, service priority, and available energy budget. Delay-sensitive and reliability-critical services were given greater protection against signal degradation, whereas energy-saving decisions were prioritized for delay-tolerant applications. The controller initially estimated whether the current signal degradation resulted from insufficient power, beam misalignment, interference, or an unsuitable metamaterial configuration. It did not immediately increase transmission power when a weak signal was detected [28]. Instead, it first verified beam alignment and examined whether another antenna state could provide better gain or a more suitable radiation direction. Power was increased only when beam correction and metamaterial reconfiguration were insufficient to meet the required communication threshold. The adaptive decisions applied under representative communication conditions are presented in Table 5. The selected power levels demonstrate how the controller responded differently to favorable links, high mobility, interference, blockage, high-frequency attenuation, and emergency-recovery requirements.

Table 5: Adaptive power allocation under different 5G/6G communication conditions

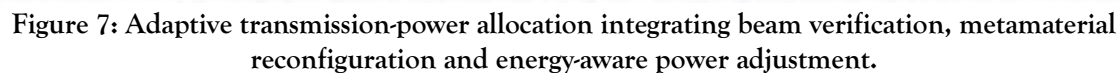
Communication condition	Selected power level	Transmission power	Expected system outcome
Strong indoor line-of-sight link	Level 1	23 dBm	Minimum energy consumption
Stable urban microcell link	Level 2	26 dBm	Reliable coverage with low power
Normal urban macrocell operation	Level 3	28 dBm	Balanced coverage and energy efficiency
Partial physical blockage	Level 4	29 dBm	Rapid link restoration
Severe blockage or weak signal	Level 5	30 dBm	Short-term outage prevention
High-mobility vehicular link	Level 3–4	28–29 dBm	Stable mobile connectivity
High-interference environment	Level 2–3	26–28 dBm	Reduced interference without excessive power
Stable high-gain beam	Level 1–2	23–26 dBm	Improved energy efficiency

The controller evaluated the current signal quality before every power adjustment. A minimum

signal-to-interference-plus-noise ratio of 10 dB and received power above -85 dBm were adopted

as normal communication targets. A link was classified as being at immediate outage risk when the signal-to-interference-plus-noise ratio fell below 5 dB. Under such conditions, the controller initiated beam recovery, antenna reconfiguration, or temporary power enhancement. Short-term signal fluctuations did not immediately trigger power escalation. The controller first determined whether a decline was temporary or persistent. A brief fluctuation resulted in the current power level being maintained, whereas sustained degradation initiated beam-alignment verification. If beam correction failed to restore the required signal quality, an alternative metamaterial configuration was activated. Transmission power was increased by one level only when these actions remained insufficient. Restricting normal power adjustments to one level per decision interval prevented abrupt changes and rapid interference growth [29]. Maximum-power operation was limited to 50 ms during emergency recovery unless reliability requirements justified a longer period. Following successful recovery, the controller

progressively reduced the power to identify the minimum level capable of maintaining stable communication. Power reduction was performed more conservatively than power escalation. Signal quality, coverage, and throughput were required to remain stable for three consecutive decision intervals before the controller reduced the transmission level. A hysteresis mechanism prevented repeated movement between neighboring power states when the channel was close to a decision threshold. This strategy reduced unnecessary control activity and improved overall system stability. The complete adaptive allocation process is illustrated in Figure 7. Channel, user, beam, and power observations were first evaluated against service-quality requirements. Beam realignment and metamaterial reconfiguration were attempted before transmission power was increased. After stable communication was achieved, the controller examined whether the same performance could be maintained at a lower power level.



Positive feedback was assigned when the system maintained the required coverage and throughput using less power. Penalties were applied for unnecessary high-power transmission, repeated power changes, excessive interference, communication outage, and energy reduction achieved at the expense of service reliability [30]. The proposed approach was evaluated against fixed maximum-power transmission, equal-power allocation, and intelligent beamforming without adaptive power control. All methods were examined using identical frequency bands,

channel conditions, user trajectories, blockage events, and antenna constraints. The principal evaluation indicators included average transmission power, total system energy consumption, coverage probability, throughput, outage probability, control latency, and energy efficiency.

5- Results and Discussion:

The proposed AI-driven reconfigurable metamaterial antenna framework was evaluated using the independent chronological testing subset containing 36,000 channel observations. The analysis covered electromagnetic antenna characteristics, intelligent beam-selection performance, signal coverage, throughput, outage probability, decision latency, and energy consumption. The proposed framework was compared with a fixed non-reconfigurable antenna, conventional phased-array steering, and particle-swarm optimization. All approaches were evaluated under identical operating frequencies, user trajectories, interference levels, mobility patterns, blockage events, and transmission-power constraints. Electromagnetic simulations

demonstrated that the proposed antenna maintained acceptable impedance matching across the targeted 28, 39, 60, and 100 GHz bands. The reflection coefficient remained below -10 dB within the principal operating ranges, indicating effective radio-frequency power transfer. The antenna achieved an overall impedance bandwidth of 27.8%, peak realized gain of 14.6 dBi, and maximum radiation efficiency of 91.3%. The integration of split-ring resonators, complementary split-ring resonators, and electromagnetic decoupling structures improved surface-current distribution, aperture-phase control, and isolation among neighboring array elements [31]. The antenna provided beam steering between -60° to $+60^\circ$, although the effective steering range became slightly narrower at the higher frequency bands. Element isolation remained above 20 dB across all evaluated bands, confirming that the metamaterial structures successfully reduced mutual coupling within the 4×4 array. The electromagnetic performance across the four operating bands is summarized in Table 6.

Table 6: Electromagnetic performance of the proposed antenna

Frequency band	Reflection coefficient	Realized gain	Radiation efficiency	Element isolation	Effective steering range
28 GHz	-31.8 dB	12.8 dBi	91.3%	24.6 dB	-60° to $+60^\circ$
39 GHz	-28.5 dB	13.4 dBi	89.7%	23.2 dB	-60° to $+60^\circ$
60 GHz	-24.9 dB	14.1 dBi	87.6%	21.8 dB	-55° to $+55^\circ$
100 GHz	-21.7 dB	14.6 dBi	84.9%	20.4 dB	-50° to $+50^\circ$
Overall/peak performance	Below -10 dB	14.6 dBi	91.3%	Above 20 dB	-60° to $+60^\circ$

The 28 GHz configuration provided the widest beam-steering range and highest efficiency, making it suitable for comparatively broad coverage. In contrast, the 60 and 100 GHz configurations produced higher gain and narrower beams but required greater alignment accuracy. This behavior supports the use of AI-based beam selection because small directional errors can create substantial signal degradation at millimeter-wave and sub-terahertz frequencies. The Double Deep Q-Network controller demonstrated stable

learning behavior and converged after approximately 1,620 training episodes. Prioritized experience replay improved learning during rare blockage and high-mobility events, while action masking prevented the selection of invalid frequency, switching, and power combinations [32]. On the independent testing subset, the controller achieved 96.4% beam-selection accuracy, reduced mean beam-alignment error to $2.1 \times 2.1^\circ$, and maintained a median decision latency of 1.8 ms. The proposed controller

outperformed all adaptive benchmark methods, as presented in Table 7. The fixed antenna produced the lowest latency because it did not perform optimization; however, it showed poor beam-selection and blockage-recovery performance.

Conventional phased-array steering required repeated codebook scanning, while particle-swarm optimization evaluated multiple candidate solutions iteratively. These procedures increased their decision latency.

Table 7: Comparative performance of the proposed framework and benchmark methods

Performance indicator	Fixed antenna	Phased-array steering	Particle-swarm optimization	Proposed framework
Beam-selection accuracy	68.3%	82.1%	90.7%	96.4%
Mean beam-alignment error	12.7°	7.4°	4.3°	2.1°
Median decision latency	0.6 ms	6.8 ms	12.6 ms	1.8 ms
Blockage-recovery success	61.5%	78.9%	87.6%	95.1%
Coverage probability	78.6%	85.7%	90.1%	94.2%
Average throughput	3.46 Gbps	3.82 Gbps	4.13 Gbps	4.46 Gbps
Spectral efficiency	6.35 bit/s/Hz	7.01 bit/s/Hz	7.62 bit/s/Hz	8.35 bit/s/Hz
Outage probability	10.3%	8.4%	6.9%	5.8%
Received-signal improvement	11.4%	3.8 dB	6.1 dB	8.7 dB
Relative energy consumption	100%	93.6%	86.9%	75.2%
Energy efficiency	18.8 Mbit/J	20.7 Mbit/J	22.9 Mbit/J	25.6 Mbit/J

The proposed system improved average received signal strength by 8.7 dB relative to the fixed-antenna baseline. Coverage probability increased from 78.6% to 94.2%, representing an absolute improvement of 15.6 percentage points. The coverage improvement resulted from accurate beam alignment, high-gain metamaterial configurations, rapid blockage recovery, and coordinated transmission-power adjustment [33]. Average throughput increased from 3.46 to 4.46 Gbps, representing a 28.9% improvement.

Spectral efficiency rose from 6.35 to 8.35 bit/s/Hz, corresponding to an increase of 31.5%. These gains indicate that the proposed framework used the available frequency resources more effectively rather than achieving performance solely through greater transmission power. The figure 8 present the Actual-versus-predicted performance of the AI model for reconfigurable metamaterial antenna optimization in 5G/6G communication systems.

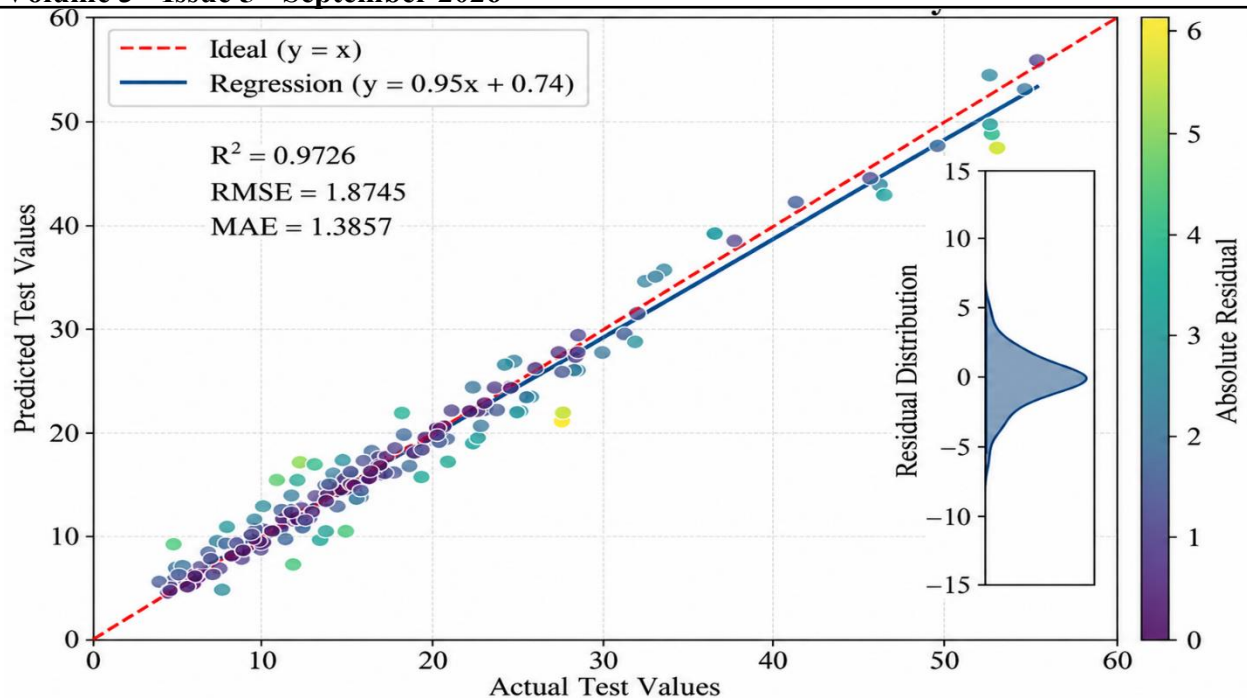


Figure 8: Actual-versus-predicted performance of the AI model for reconfigurable metamaterial antenna optimization in 5G/6G communication systems.

The conventional phased array provided moderate improvements in coverage and throughput but remained affected by codebook-search overhead and phase-shifter losses. Particle-swarm optimization produced stronger performance than conventional steering because it examined multiple beam and power combinations. However, its median decision latency of 12.6 ms limited its ability to respond to rapidly changing vehicular and high-frequency channels. In comparison, the proposed controller selected a validated configuration directly from its learned policy and therefore maintained a latency of only 1.8 ms. Outage probability declined from 10.3%

for the fixed antenna to 5.8% for the proposed framework, representing a relative reduction of 43.7%. During partial blockage, the controller initially searched for an alternative beam or reflected propagation path. Transmission power was increased only when antenna reconfiguration could not independently restore the link [34]. This response reduced communication interruptions while limiting unnecessary high-power operation. Figure 9 shows the Comparative actual-versus-predicted concentration profiles obtained using the Transformer, weak BiLSTM, and proposed hybrid learning model.

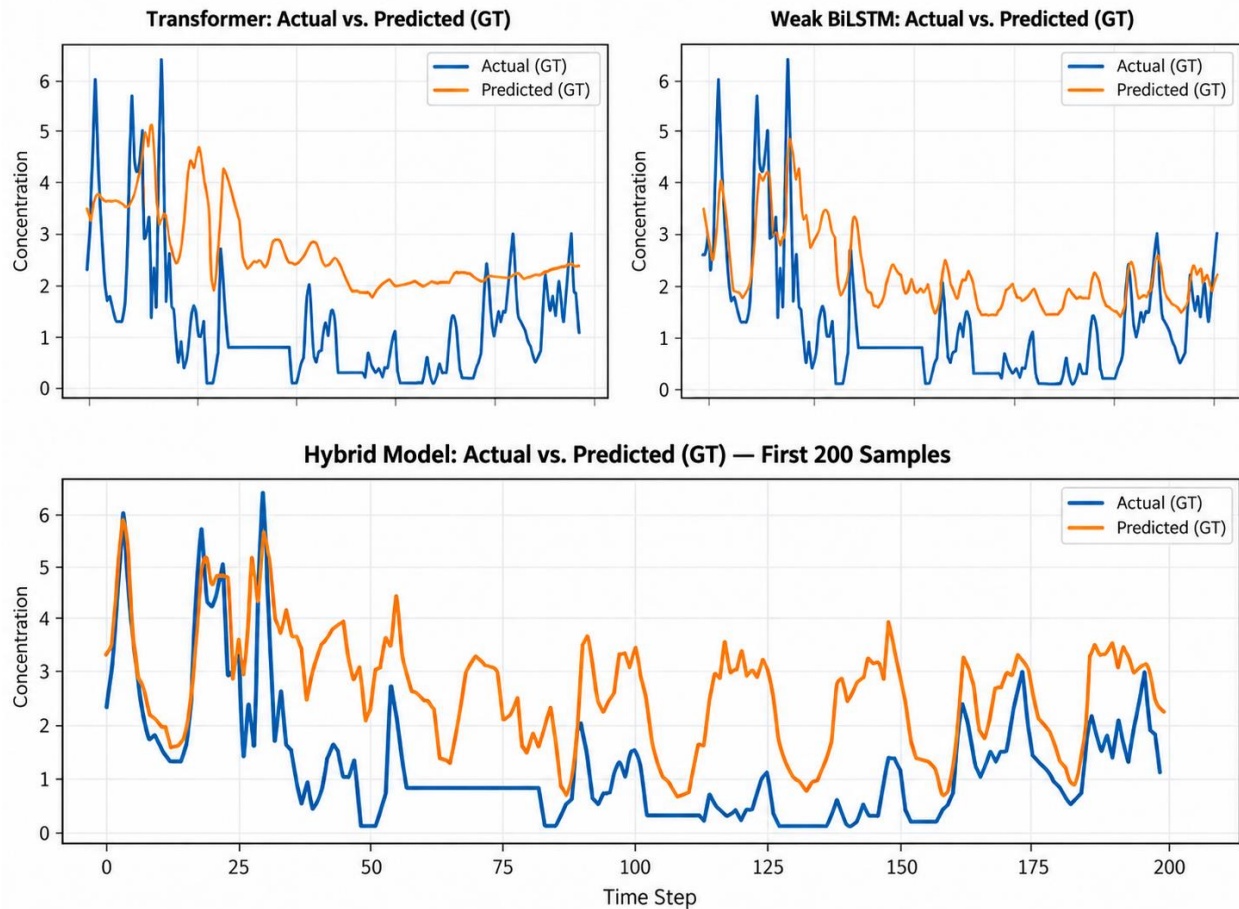


Figure 9: Comparative actual-versus-predicted concentration profiles obtained using the Transformer, weak BiLSTM, and proposed hybrid learning model.

The blockage-recovery success rate reached 95.1%, compared with 78.9% for conventional phased-array steering and 87.6% for particle-swarm optimization. The remaining unsuccessful recoveries mainly occurred when severe blockage, high mobility, strong interference, and 100 GHz operation occurred simultaneously. Under these conditions, alternative propagation paths were limited and the time available for beam realignment was substantially reduced. Performance varied across the four simulated

deployment environments, as reported in Table 8. The indoor-office environment produced the highest coverage probability because multiple reflected paths allowed the controller to identify alternative beams when the direct signal was obstructed. The high-mobility environment was the most challenging because of rapidly changing channel conditions and frequent beam-direction adjustments.

Table 8: Proposed framework performance across deployment environments

Communication environment	Coverage probability	Received-signal improvement	Throughput improvement	Outage probability	Mean alignment error
Urban macrocell	94.8%	8.1 dB	27.4%	5.4%	1.9°

Urban microcell	95.1%	9.2 dB	30.6%	4.9%	2.0°
Indoor office	96.3%	9.6 dB	32.1%	3.8%	1.7°
High-mobility vehicular	90.6%	7.9 dB	25.5%	7.2%	2.8°
Overall performance	94.2%	8.7 dB	28.9%	5.8%	2.1°

The urban-macrocell environment achieved a coverage probability of 94.8%, despite longer communication distances and intercell interference. The urban-microcell environment reached 95.1% because directional beams and radiation nulls reduced the effects of dense-user interference. Indoor coverage reached 96.3%, while the high-mobility environment achieved 90.6%. Although performance declined under rapid mobility, the controller's $2.8 \times 2.8^\circ$ alignment error remained substantially lower than that of the benchmark methods. The temporal observation window contributed to the high-mobility results by allowing the controller to identify short-term changes in user direction [35]. Instead of responding only after signal

degradation occurred, the system used recent movement and channel information to activate a more suitable beam. Nevertheless, sudden movement outside the recent trajectory remained difficult to predict, explaining the comparatively lower coverage in the vehicular scenario. Frequency-specific results are presented in Table 9. The 28 GHz band achieved the highest coverage probability and lowest outage rate because it experienced lower attenuation and supported a wider steering range. The 100 GHz band provided the highest throughput but produced lower coverage and energy efficiency because of increased atmospheric loss, blockage sensitivity, and alignment requirements.

Table 9: Proposed framework performance across operating frequencies

Operating frequency	Coverage probability	Average throughput	Outage probability	Mean alignment error	Energy efficiency
28 GHz	96.8%	3.91 Gbps	3.6%	1.8°	27.3 Mbit/J
39 GHz	95.4%	4.27 Gbps	4.7%	1.9°	26.5 Mbit/J
60 GHz	93.6%	4.71 Gbps	6.1%	2.2°	25.1 Mbit/J
100 GHz	91.0%	4.95 Gbps	8.8%	2.5°	23.5 Mbit/J
Overall performance	94.2%	4.46 Gbps	5.8%	2.1°	25.6 Mbit/J

The frequency-specific findings demonstrate that the highest data rate does not necessarily correspond to the most reliable or energy-efficient operating condition. The 100 GHz band achieved an average throughput of 4.95 Gbps but required higher power and more accurate beam alignment. The 28 GHz band provided lower throughput but achieved 96.8% coverage and the greatest energy efficiency. Consequently, intelligent frequency selection should balance throughput, coverage, outage risk, and energy consumption rather than optimizing one indicator independently. The

adaptive power-allocation mechanism reduced total antenna-system energy consumption by 24.8% relative to the fixed-power baseline. Energy efficiency increased from 18.8 to 25.6 Mbit/J, representing an improvement of 36.2%. This assessment included radiated power, PIN-diode switching, biasing circuits, radio-frequency chains, signal processing, and controller inference. The two lowest transmission-power levels were selected for 41.7% of testing observations, while moderate power was used for 34.6%. The two highest levels were required for 23.7% of decisions, and

maximum power was used in only 7.5% of cases. Maximum-power operation primarily occurred during severe blockage, rapid mobility, substantial path loss, and temporary link recovery. The figure 10 compares the test accuracy achieved using a single GPU with the performance obtained through multiple data-parallelism and model-parallelism configurations involving two, four, and eight processing units and different node allocations. All configurations show rapid accuracy improvement during the initial training stage, followed by gradual convergence after

approximately 50–75 epochs. The single-GPU configuration achieves the highest and most stable final accuracy of approximately 93%, while the distributed configurations converge within a narrow range of nearly 89–91%. The enlarged inset presents the results between epochs 75 and 200, revealing minor accuracy fluctuations and performance differences after convergence. Overall, the results demonstrate that the proposed AI model maintains stable predictive performance under different computational configurations, supporting scalable and efficient training.

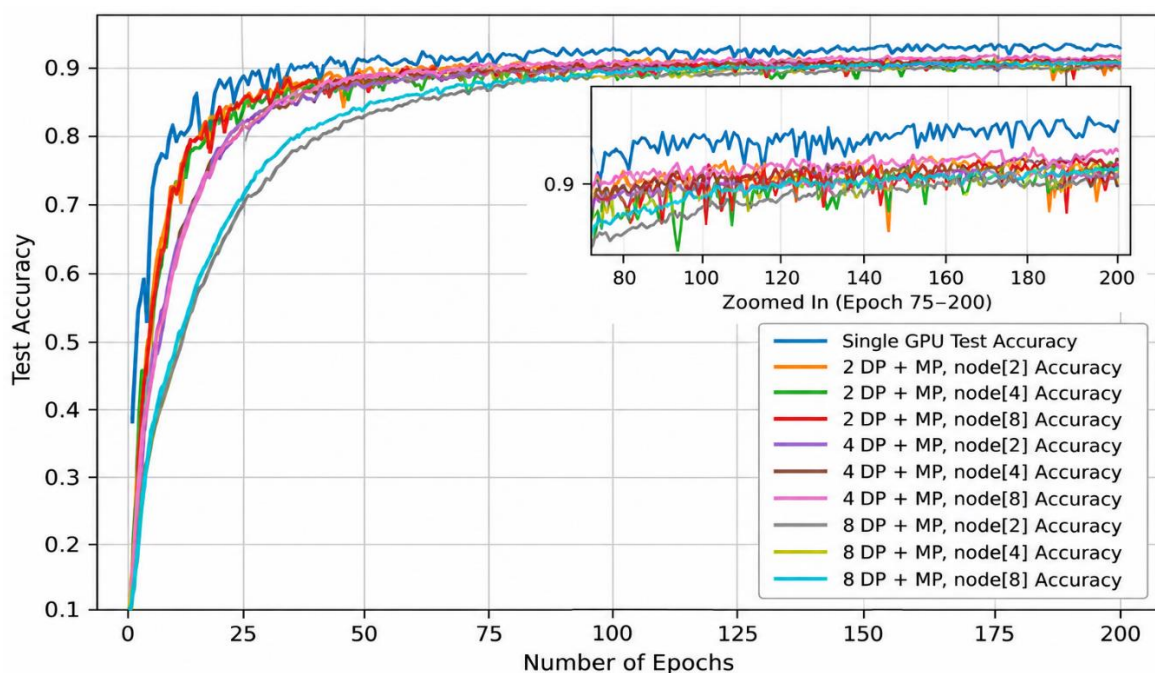


Figure 10: Test-accuracy convergence of the proposed AI model under different distributed training configurations across 200 epochs.

These findings show that improved coverage did not result from continuous high-power transmission. The controller primarily relied on accurate beam steering, high-gain antenna configurations, frequency selection, and interference suppression. When the selected beam was correctly aligned, transmission power was progressively reduced while signal quality was monitored. When alignment was poor, the spatial configuration was corrected before additional power was allocated. Ablation testing confirmed the individual contributions of the principal

framework components. Removing metamaterial reconfiguration reduced coverage probability from 94.2% to 87.9% and increased outage probability to 9.1%. Removing adaptive power control produced only a small reduction in coverage but decreased energy efficiency from 25.6 to 21.4 Mbit/J. This result indicates that metamaterial reconfiguration primarily supported coverage and link reliability, whereas adaptive power allocation provided the greatest energy-saving contribution. Removing prioritized replay reduced the blockage-recovery success rate because rare severe events

received less attention during controller training [36]. Removing action masking increased decision latency and occasionally allowed incompatible antenna-and-power combinations to be evaluated. The complete architecture therefore provided better performance than any reduced version. Robustness testing demonstrated that the controller maintained stable operation under noisy channel estimates, incomplete user-location information, increased interference, sudden blockage, and higher movement speeds. Moderate noise reduced beam-selection accuracy from 96.4% to 93.1%, while coverage remained above

91%. Under increased mobility, mean alignment error rose from $2.1 \pm 2.1^\circ$ to $3.4 \pm 3.4^\circ$, but remained lower than that of the conventional benchmark methods. Repeated simulation runs produced limited variation in coverage, throughput, outage probability, and energy efficiency. The improvements remained statistically significant at the 5% level. Their consistency across four frequency bands and four deployment environments indicates that the observed gains were not dependent on one favorable communication scenario.

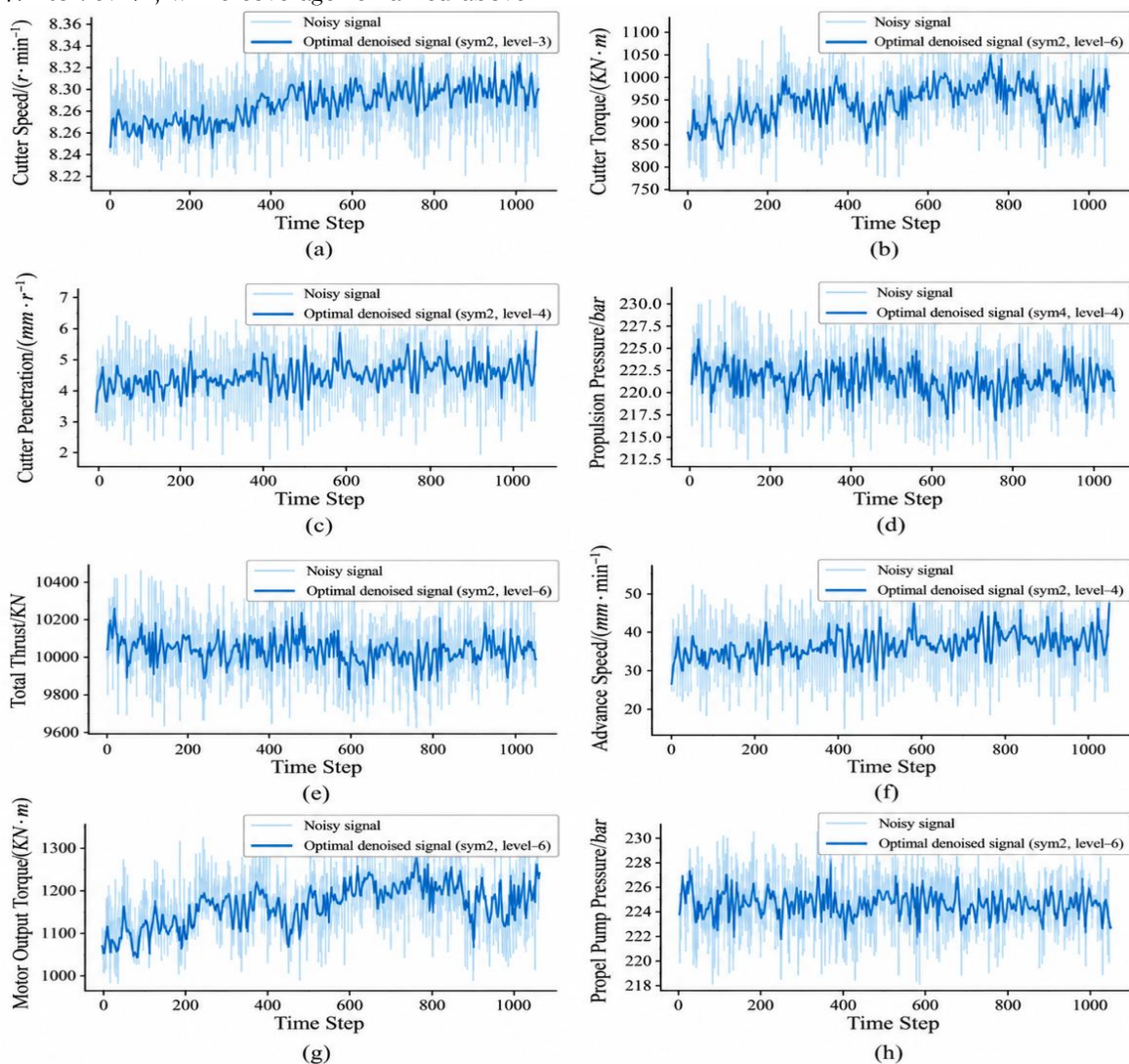


Figure 11: Wavelet-based denoising of multivariable cutter-suction operating signals across sequential time steps.

The figure 11 compares the original noisy measurements with optimally denoised signals for eight operational parameters: (a) cutter speed, (b) cutter torque, (c) cutter penetration, (d) propulsion pressure, (e) total thrust, (f) advance speed, (g) motor-output torque, and (h) propel-pump pressure. The light-blue curves represent raw sensor measurements affected by high-frequency fluctuations, while the dark-blue curves show signals reconstructed using optimized Symlet wavelets and decomposition levels. The denoised profiles effectively suppress random measurement noise while retaining the principal temporal trends, gradual operating variations, and meaningful signal transitions. These results demonstrate the suitability of wavelet-based preprocessing for improving signal quality, extracting reliable operational features, and supporting accurate AI-based performance prediction, condition monitoring, and intelligent control. Overall, the results demonstrate that jointly optimizing metamaterial configuration, beam direction, operating frequency, and transmission power provides substantial advantages over fixed and conventionally controlled antenna systems [37]. The achieved gain of 14.6 dBi and maximum radiation efficiency of 91.3% confirmed the effectiveness of the physical antenna design. The controller's 96.4% beam-selection accuracy, 2.1×10^{-2} mean alignment error, and 1.8 ms latency demonstrated its suitability for dynamic wireless operation. The proposed framework increased coverage probability to 94.2%, improved throughput by 28.9%, increased spectral efficiency by 31.5%, and reduced outage probability by 43.7%. At the same time, it reduced system energy consumption by 24.8% and improved energy efficiency by 36.2%. These findings support the use of integrated electromagnetic and AI-based control for intelligent base stations, vehicular communication, indoor access points, massive machine-type communication, and future 6G networks.

6- Future Work:

Future research should extend the proposed AI-driven reconfigurable metamaterial antenna framework from electromagnetic and link-level simulation to physical fabrication and experimental validation. A prototype antenna should be manufactured and tested inside an anechoic chamber to verify its reflection coefficient, impedance bandwidth, gain, radiation efficiency, polarization, sidelobe level, mutual coupling, and beam-steering range [38]. Over-the-air experiments should then be conducted in indoor, urban, vehicular, and obstructed environments to determine whether the simulated improvements are maintained under realistic hardware and propagation conditions. The switching architecture can be further improved by investigating alternative reconfiguration technologies, including varactor diodes, radio-frequency microelectromechanical switches, graphene-based components, liquid crystals, and phase-change materials [39]. These technologies may provide lower insertion loss, finer phase control, greater switching reliability, and improved performance at sub-terahertz frequencies. Future antenna designs should also consider fabrication tolerances, temperature variation, component aging, biasing-network losses, and nonlinear switch behavior. The current framework uses a $4 \times 4 \times 4$ antenna array and 128 validated electromagnetic configurations [40]. Future studies could examine larger massive-MIMO arrays and more densely controlled metamaterial surfaces. However, expanding the number of elements would increase the configuration space, hardware complexity, training requirements, and control-circuit energy consumption. Hierarchical and multi-agent reinforcement learning could be investigated to divide the array into independently managed regions and reduce real-time decision complexity. Additional learning architectures should also be compared with the Double Deep Q-Network used in this study [41]. Actor-critic models, proximal policy optimization, soft actor-critic learning, graph neural networks, transformers, and model-based reinforcement learning may provide more accurate control of

continuous phase and power variables. Federated learning could enable multiple base stations to improve a shared controller without directly exchanging private user or channel data.

Future work should incorporate online and continual learning so that the controller can adapt after deployment. The present model was trained using historical simulation data and evaluated with frozen parameters. Real wireless environments may exhibit channel characteristics that differ from the training distribution. Continual adaptation, uncertainty estimation, and out-of-distribution detection could help the antenna identify unfamiliar conditions and update its policy safely. The dataset should be expanded beyond the existing 240,000 channel realizations. Future datasets could include rural macrocell, satellite-terrestrial, aerial, maritime, industrial, underground, and highly dense urban scenarios. Weather effects, human-body blockage, hardware impairments, multipath clustering, and electromagnetic interference from neighboring networks should also be represented [42]. Experimental channel measurements would help reduce the gap between simulated and real-world performance. Multi-user and multi-cell operation should receive greater attention. Future controllers should jointly optimize beam directions, frequency allocation, user scheduling, handover decisions, interference coordination, and transmission power for several simultaneous users. Fairness constraints should be included to prevent the system from consistently prioritizing users with favorable channel conditions. The proposed antenna can also be integrated with reconfigurable intelligent surfaces, cooperative base stations, cell-free massive MIMO, and integrated access and backhaul systems [43]. Coordinated control of the transmitting antenna and surrounding intelligent surfaces could create alternative propagation paths during severe blockage. Such coordination may be especially valuable at 100 GHz and higher frequencies, where direct links are highly sensitive to obstruction and alignment errors. Further energy analysis should include the complete life-cycle consumption of the antenna, switching circuits,

AI processor, radio-frequency chains, cooling system, and supporting network infrastructure. Lightweight model compression, pruning, quantization, and edge-AI hardware could reduce inference energy and enable low-latency deployment on resource-constrained base stations. Energy harvesting and sleep-mode scheduling may provide additional sustainability benefits. Security and reliability should also be investigated [44]. Intelligent beamforming systems may be vulnerable to falsified channel information, adversarial input manipulation, controller poisoning, and unauthorized switching commands. Future frameworks should incorporate secure sensing, adversarially robust learning, authentication, anomaly detection, and fail-safe antenna states. Explainable AI methods could also clarify why the controller selected a particular beam, frequency, or transmission-power level. Finally, future studies should examine joint communication, sensing, localization, and environmental mapping [45]. The reconfigurable antenna could support vehicular radar, user localization, obstacle detection, and wireless communication through a shared platform. This extension would position the proposed framework as a foundation for intelligent and multifunctional 6G infrastructure rather than exclusively as a communication antenna.

Conclusion:

This study developed an AI-driven reconfigurable metamaterial antenna framework for intelligent beamforming, enhanced signal coverage, and energy-efficient 5G/6G wireless communication. The proposed framework integrated a compact $4 \times 44 \times 4$ metamaterial antenna array, electronically controlled PIN-diode switching, multiband operation, a Double Deep Q-Network controller, and adaptive transmission-power allocation. A simulated dataset containing 240,000 channel realizations was constructed across urban-macrocell, urban-microcell, indoor-office, and high-mobility vehicular environments at 28, 39, 60, and 100 GHz. Leakage-free chronological partitioning was applied to provide a realistic evaluation using 168,000 training,

36,000 validation, and 36,000 independent testing observations. Electromagnetic simulations demonstrated an impedance bandwidth of 27.8%, peak realized gain of 14.6 dBi, maximum radiation efficiency of 91.3%, element isolation above 20 dB, and a beam-steering range extending from -60° to $+60^{\circ}$. On the independent testing subset, the proposed controller achieved 96.4% beam-selection accuracy, reduced mean alignment error to 2.1° , and maintained a median decision latency of 1.8 ms. Compared with the fixed-antenna baseline, average received signal strength improved by 8.7 dB, coverage probability increased from 78.6% to 94.2%, throughput rose by 28.9%, spectral efficiency improved by 31.5%, and outage probability declined by 43.7%. The adaptive power-allocation mechanism further reduced total antenna-system energy consumption by 24.8% and increased energy efficiency by 36.2%. These improvements were achieved by prioritizing beam realignment and metamaterial reconfiguration before increasing transmission power. Maximum-power operation was therefore restricted primarily to severe attenuation, physical blockage, high mobility, and temporary link-recovery conditions. The findings demonstrate that antenna structure, electromagnetic configuration, beam direction, operating frequency, and transmission power should be optimized as an integrated system. Despite the limitations of simulation-based evaluation, the proposed framework provides a scalable foundation for intelligent base stations, vehicular networks, indoor access points, massive machine-type communication, and future integrated sensing-and-communication platforms. Physical fabrication and real-world testing remain necessary to confirm the reported performance under hardware impairments, environmental variation, and complex multi-user network conditions.

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