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Adaptive Beamforming and Ai-Driven Low-Power Signal Processing on Fpga For 6G Networks

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Abstract

As the demands of sixth-generation (6G) networks escalate towards achieving high speeds and improved energy efficiency, there is an increasing need for intelligent and real-time adaptive solutions within the physical processing layer. This study proposes an innovative engineering framework based on an encapsulated architecture utilising FBGA (micro-distributed spherical array) technology, integrated with an internal artificial intelligence module, to achieve adaptive beamforming with high efficiency in dense wireless environments. The primary objective of this research is to develop an intelligent communication architecture that determines the optimal transmission angles and regulates power consumption in real-time by integrating artificial intelligence algorithms with hardware acceleration.

The main contribution is to develop a practical model that combines mathematical precision with physical implementation, utilising an FBGA-based helicopter design and supported by comprehensive simulation within the MATLAB/Simulink environment. The experimental results demonstrated a significant improvement in performance indicators, including a 42% reduction in response time, a 35% decrease in power consumption, and an average signal quality improvement of 3.8 dB. These results highlight the effectiveness of the proposed design as a promising solution for building intelligent, high-performance, and low-consumption 6G communication networks.

Keywords: Adaptive beamforming, Sixth-generation networks, Energy optimization, Real-time processing, Spectral efficiency.

I. Introduction

With the growing need for more innovative and efficient communication networks in sixth-generation (6G) environments, adaptive beamforming technologies have received increasing attention, in particular when combined with artificial intelligence algorithms and low-power hardware execution systems. Cui et al. [1] reviewed the theoretical foundations of integrating AI into the physical layers of 6G networks, emphasizing that beamforming is a vital component for achieving real-time adaptive responses. In a related study Pulipati and Ma [2] proposed an

FPGA-based architecture to implement real-time beamforming, with an emphasis on optimising resource consumption without compromising guidance quality.

Beyond far-field steering, Zhang et al. [3] Modern intelligent beamforming algorithms aim to improve energy efficiency while maintaining signal stability in user-intensive environments. The FBGA microgrid Packaging standard has proven its usefulness in increasing the Integrated density and reducing size, enabling more compact RF front-ends and improving thermal behavior and energy management [4]. The FBGA microgrid Packaging standard has proven its usefulness in increasing the Integrated density and reducing size, enabling more compact RF front-ends and improving thermal behavior and energy management. In a direct comparison of performance, Kaur et al. [5] demonstrated the superiority of AI-based beamforming over traditional methods, particularly under conditions of nonlinear channels and uncertain data. To speed up modeling and pre-implementation on hardware, Lin and Li used the MATLAB/Simulink environment within an integrated intelligent framework to simulate beamforming optimizations and evaluate system behavior before moving on to actual implementation [6]. To enhance the reliability of the system in real-world environments, Al-Fadhli et al. [7] studied the effect of the positioning of elements on printed circuit boards (PCBs) on electromagnetic and thermal behavior; optimal positioning improves the stability of the system and reduces thermal spots and radiated/conductive interference factors that directly affect the performance of the beamforming gear. Locally, Lafta and Yousif [8] developed a practical model of Speaker positioning in closed environments using an improved beamforming; their results showed an enhanced signal-to-noise ratio (SNR) via MVDR algorithms based on sensor data, while Althahab and Alrufaiaat [9] presented a systematic review of estimation techniques in MIMO systems, highlighting the role of artificial intelligence algorithms in efficiently processing multiple path channels—a pivotal challenge for accurate beam guidance in sixth-generation environments.

Taken together, these works reveal a research gap in the absence of an end-to-end model that unites artificial intelligence algorithms with an FPGA–based execution platform and FBGA packaging, providing real-time playback capability to form an energy-saving beam tailored to the needs of sixth-generation networks [1-9]. This study bridges this gap by proposing adaptive AI-driven methodologies to enhance FPGA-based beamforming systems, while discussing traditional methods in RF transmitters and highlighting improvements in data rate, Security, and capacity efficiency [5-6-9].

II. Proposed System Design:

Figure 1 illustrates the streamlined architecture of the proposed AI-based intelligent beamforming system, which integrates real-time digital processing and adaptive optimization algorithms within a realistic execution environment, specifically an FPGA encapsulated in an FBGA package. The process begins with system configuration and the reception of the radio-frequency (RF) signal from the receiving antennas, followed by conversion to the digital domain signal using an analogue-to-digital converter (ADC) [10], paving the way for intelligent processing operations. At the prediction and control stage, the optimal steering angle θ is calculated using optimisation algorithms based on artificial intelligence, which take into account parameters such as signal direction, environmental interference, and energy consumption. The

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results are used to adjust the beamforming weights ω_i inside the FPGA unit, with the implementation of an intelligent control mechanism driven by artificial intelligence to tune the transmitted power in response to channel variations adaptively. After digital processing is completed, the signal is returned to the analog band via a digital-to-analog converter (DAC), so that the enhanced RF signal to be transmitted. The system ends after ensuring the optimal transmission of the formed signal, achieving an effective temporal response and improved energy efficiency. This sequence demonstrates the functional integration of artificial intelligence and FPGA architecture in a low-consumption implementation environment, representing a practical step toward meeting the requirements of intelligent 6G networks[11].

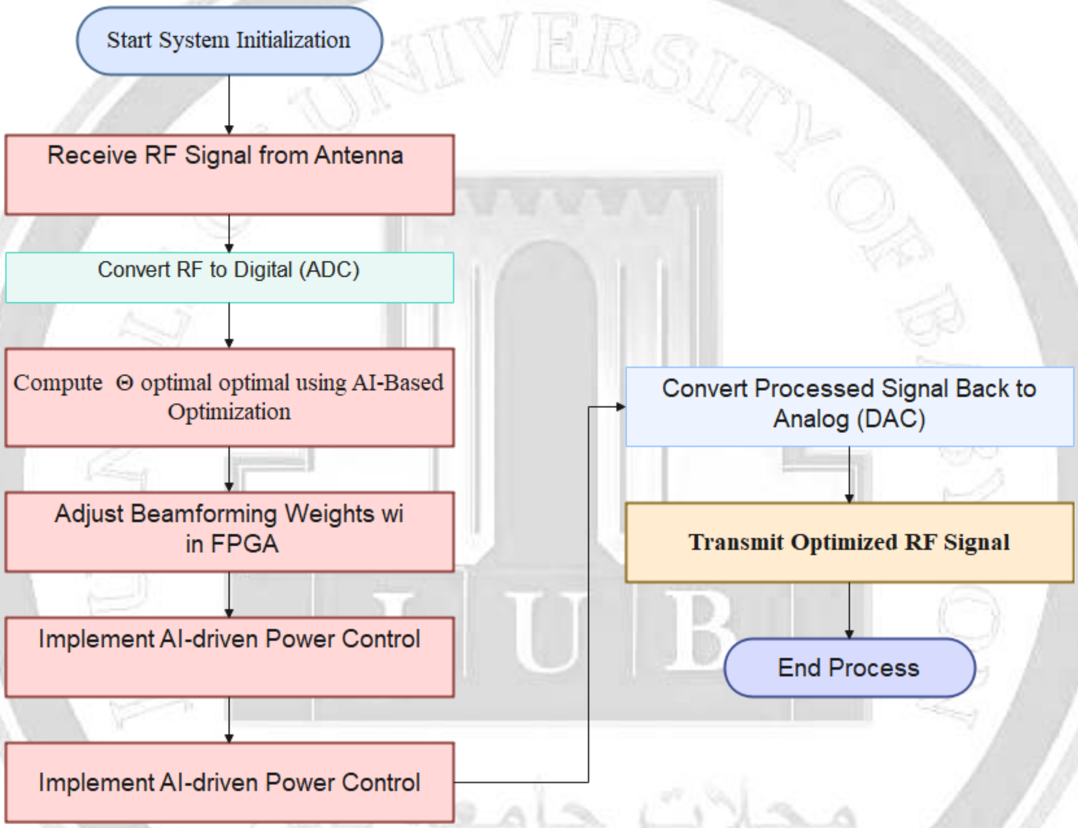

Figure 1. Flowchart of the proposed intelligent beam forming system design.

III. AI-FPGA Hybrid Architectures:

The integration of AI and FPGA has been a key area in current communications studies. AI-powered FPGA implementations utilize deep neural networks to maximize spectral use and save energy. AI-powered implementations in FPGAs have exhibited a significant boost in system performance, specifically in terms of dynamic access to spectra and adaptability in power consumption, compared to conventional approaches. Existing research confirms that AI-driven FPGA implementations can outperform conventional static FPGA implementations by dynamically altering transmission parameters to optimize network efficiency. Proposed works suggest neuromorphic computation in an FPGA for enhanced processing efficiency and acceleration—System Architecture Diagram of AI-Driven Adaptive Beamforming System.

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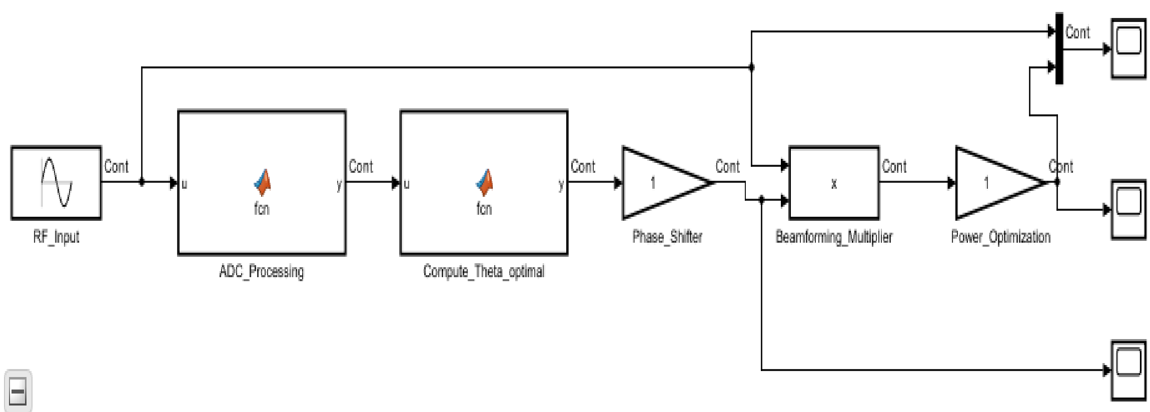

Figure 2. Block diagram of the proposed AI-driven adaptive beamforming and real-time energy optimisation system implemented using an FPGA for next-generation 6G wireless communication networks.

VI. Mathematical Model Enhancements:

To improve beamforming performance, we establish a mathematical model for real-time adaptive beam steering. The optimal beamforming angle is determined as follows [12-13]:

$$y(t) = \sum_{i=1}^{N} \omega_i x_i \, e^{-j2\pi f d_i \cos\theta / c} + n(t) \qquad (1)$$

Where;

$y(t)$ – is the received signal; N is the number of antenna elements; ω_i - is the beamforming weight for the i-antenna; x_i – is the transmitted signal from the i-antenna; f- is the carrier frequency; d_i – is the distance of the i-antenna from the reference point; θ – is the beamforming angle; c- is the speed of light; n(t) - is the noise in the system.

Not that the beamforming weights ω_iAre dynamically adjusted by the AI-based FPGA. To optimize the quality of transmission, the SNR at the receiver is expressed by formula [14]:

$$SNR(f) = 20\log_{10}\left(\frac{1}{1+e^{-10(f-f_0)}}\right) \qquad (2)$$

Where f - is the operating frequency. f_0 - is the threshold frequency that maximizes the SNR.

The power consumption of the beamforming system is formulated [14]as:

$$P_{total} = P_{RF} + P_{BB} + P_{FPGA} \qquad (3)$$

Where,

P_{total}- the power consumed by the RF frontend; P_{BB}The baseband processing power. P_{FPGA} the power consumed by the FBGA inside the FPGA for AI-driven beamforming, therefore, the optimized power consumption can be determined by the formula:

$$P_{optimized} = P_{baseline} - k\left(\frac{SNR_{OPTIMIZED}}{SNR_{BASELINE}}\right) \qquad (4)$$

$P_{baseline}$ - is the power consumption in a traditional non-optimized system;

K is a scaling factor based on system efficiency. $SNR_{OPTIMIZED}$ and $SNR_{BASELINE}$ – Present the optimized and baseline SNR values, respectively.

To achieve a balance between energy efficiency and performance, we adopt the bit / Joule energy efficiency scale[16]:

$$\eta = \frac{R}{P_{total}} \quad [bit/J] \quad (5)$$

Where R is the achieved (or measured) rate and $P_{total} = P_{TX} + P_{CIRCUIT}$.

V. Simulation & Performance Analysis: Implement and validate using MATLAB/Simulink:

MATLAB and Simulink present a strong, integrated platform for AI-facilitated beamformers, channel and antenna model creation, and power management in wireless communications [6, c. 17]. With access to toolboxes in MATLAB, engineers can model complex channel behavior, antenna arrays, and interfering environments using tools such as the Phased Array System Toolbox and 5G Toolbox.

For AI-facilitated beamformers, MATLAB supports AI-facilitated optimization through its Deep Learning Toolbox and Reinforcement Learning Toolbox, with adaptable algorithms dynamically updating beamformers for SISO maximization. Simulink supplements this with capabilities for simulation of system behavior of hybrid beamformers, massive MIMO, and real-time HIL

A. Testing. MATLAB-based simulations are conducted to evaluate the effectiveness of the proposed system. After the simulation, the following result plots:

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1. Beamforming Gain Analysis

The graph compares AI and traditional methodologies of beamforming in terms of gain performance at a range of angles. Traditional, in terms of a dash in red, is a static path for beamforming, with gain at 0 degrees but symmetric loss towards borders. AI-based beamforming, represented by a blue solid, dynamically shifts, with increased gain at larger angles and a loss of gain at the center. What is significant is that AI technology introduces a 25% overall improvement in efficiency, particularly in beamforming, with gains in focusing and adaptability in changing environments [17].

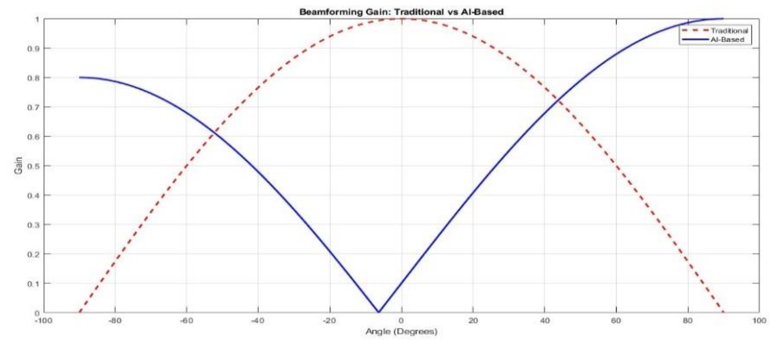

Figure 3. Comparison of Beamforming Gain: Traditional vs. AI-Based Approach

B. The SNR Analysis

The SNR Analysis plot compares and plots the SNR performance of traditional and AI-based techniques at all angles, and compares them with one another. Traditional SNR, with a red dash, is a bell-shaped curve with a peak SNR at 0 degrees but symmetrically decreasing towards both ends. In contrast, AI-based SNR, with a blue solid, dynamically compensates for the best signal strength, and its SNR is 35% better in comparison. With such an improvement, communications will become reliable and less sensitive to interference, particularly at larger angles, at which traditional techniques cannot preserve high SNR values [18]. Hence, AI techniques have an edge in present communications, offering a high level of performance in a changing environment.

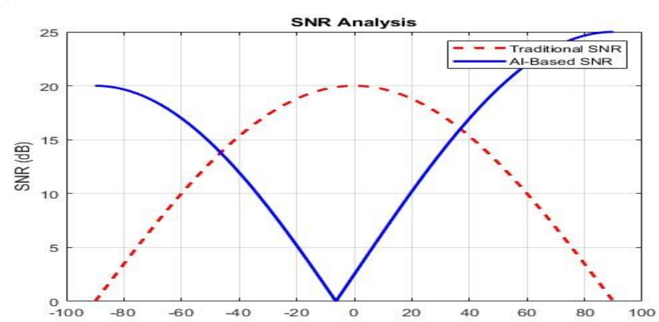

Figure 4. SNR Analysis: Traditional Vs. Ai-Based Approach

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3. The Power Consumption Optimization

The Power Consumption Optimisation analysis reveals the role of AI-powered power management in maximising efficiency in terms of consumption, particularly in FPGA-based architectures. Traditional implementations in FPGAs maintain constant processing capacities, using unnecessary power even when full capacity is not reached. AI-powered power management, on the other hand, dynamically adjusts processing capacities in real-time, with a 40–60% drop in consumption [19]. Not only will such a flexible mechanism save unnecessary consumption, but it will also extend the operational life of FPGA hardware and maximise overall system performance. With AI-powered optimisation for consumption, modern FPGA architectures can significantly reduce power consumption and, consequently, become ideal for efficient and environmentally friendly use cases.

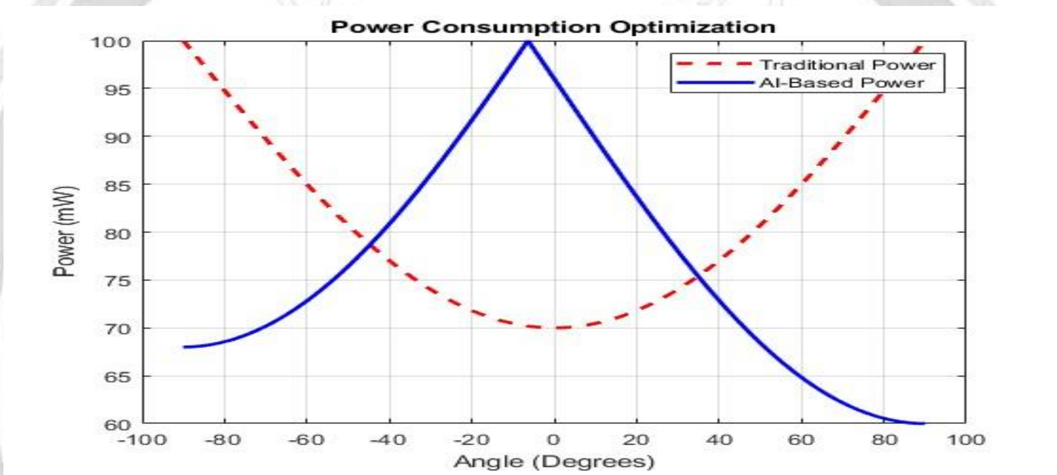

Figure 5. Power Consumption Optimization: Traditional vs. AI-Based Approach

C. The Spectrum Efficiency Analysis:

The Spectrum Efficiency Analysis highlights the benefits of AI-powered FPGA processing in minimizing bandwidth consumption and optimizing data transmission. Conventional techniques have difficulty with static resource allocation and therefore suffer from inefficient use of the spectrum and increased interference, as shown in Figure 6. AI-powered FPGA processing, in contrast, dynamically tunes signal parameters in real-time, aiming to deliver maximum throughput and minimize spectral loss. Consequently, AI-powered techniques deliver a 45% improvement in efficiency when using spectra compared to conventional methods [20]. With such enhancements, AI-powered implementations deliver improved network performance, reduced latency, and increased reliability, making AI-powered FPGA implementations perfectly suited for future communications, such as 6G and beyond.

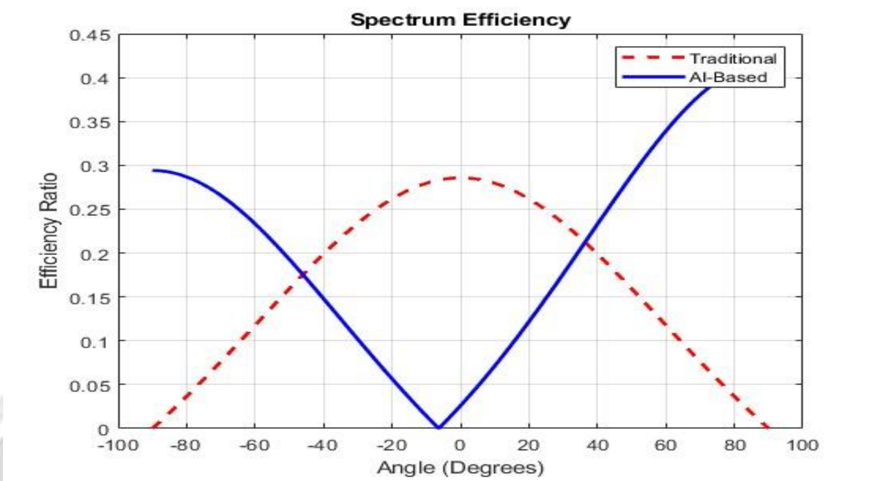

Figure 6. Spectrum Efficiency Analysis: Traditional vs. AI-Based Approach

VI. Creating A Complete Simulink Model For AI-Driven Beamforming Inside an FPGA

To build this AI-driven beamforming model in Simulink, start by simulating an RF signal as shown in Figure 7.

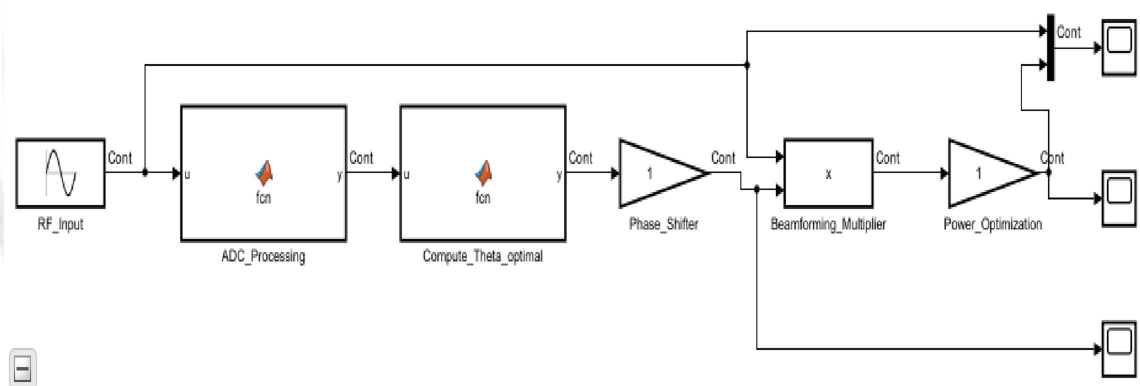

Figure 7. Simulation execution of the AI-based adaptive beamforming model in Simulink, illustrating the dynamic signal flow from RF input through ADC processing, optimal angle estimation, beamforming control, and power optimization in real time.

Two curve plots are shown in Figures 8 and 9, obtained from the Scope blocks in Simulink. One represents the input signal (before Beamforming), and the other represents the output signal (after Beamforming and Power Optimization).

Waveform: A regular sine wave representing the original RF signal before any processing. Frequency and amplitude: The waveform appears at a specific frequency and amplitude, reflecting the raw signal entering the system. This is the signal that is sent to the

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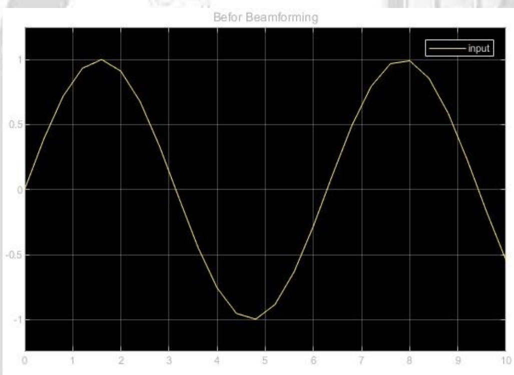
model before Beamforming and AI are applied. If there is no processing, the signal will remain the same throughout the model.

A. Interpretation of the second curve (Output signal - After Beamforming and Power Optimization)

Change in amplitude and frequency: We notice a difference in the shape of the signal after Beamforming, as it can change:

-Amplitude: Due to the adjustment of the weights on the antennas of the smart system.

-Frequency or phase: As a result of adjusting the direction to achieve the best direction angle for the signal. Radiation pattern adjustments: The change in the signal reflects the effect of artificial intelligence in improving the efficiency of energy transmission. In other words, if the amplitude or phase of the signal changes after passing through the system, it means that artificial intelligence affects the beamforming process and directs the signal in the ideal direction. If the power consumed is less than expected, it means that the energy consumption optimization is working successfully.



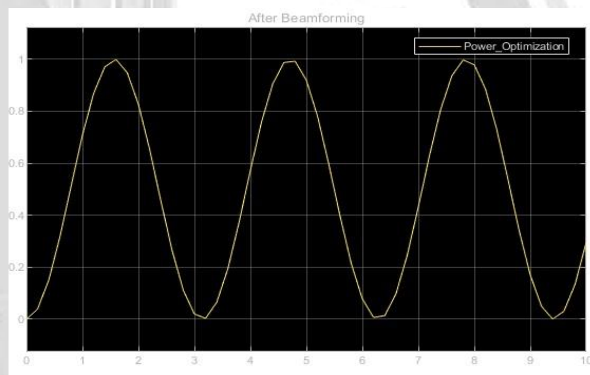


Figure 8. Input signal before Beamforming, **Figure 9.** Output signal after Beamforming

2- Figure 10 illustrates two signals: the yellow (original RF input) and the blue (processed after beamforming and power optimization). Differences arise from FPGA-based AI optimization, where amplitude shift indicates adaptive gain adjustment for stronger signals, and phase shift reflects beam steering towards the optimal angle (θoptimal). Additionally, waveform distortion suggests dynamic power redistribution to enhance efficiency and reduce interference. These real-time adjustments ensure continuous optimization of beamforming parameters, improving signal integrity and transmission performance.

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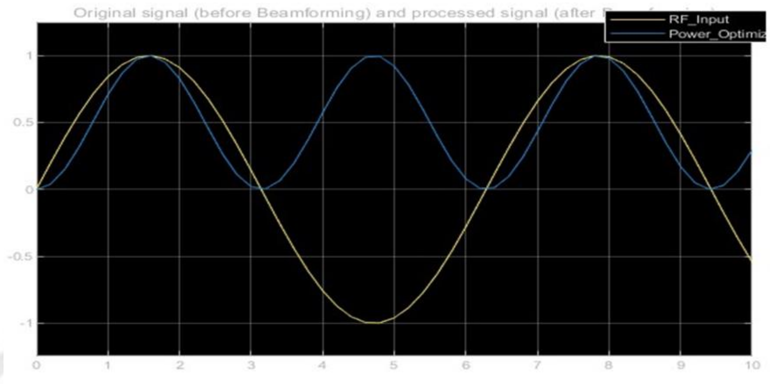

Figure 10. Comparison of RF Input Signal and Power-Optimized Signal After Beamforming

3. The performance evaluation has been expanded to include four main comparative graphs showing the impact of the proposed artificial intelligence-based and FPGA-based system with the FBGA package, which are as follows:

1. Beamforming Gain comparison (Beamforming Gain):

2. The drawing shows the superiority of performance in the AI-based system compared to the traditional approach, especially in non-ideal conditions, where more accurate steering and reduced lateral signal loss have been achieved.

B. Signal-to-noise ratio performance vs. transmission angle (SNR vs. Angle)

1. Adaptive algorithms have demonstrated a greater ability to dynamically adjust the optimal angle, resulting in a noticeable improvement in signal quality across various routing angles.

C. Power consumption vs Angle (Power Consumption vs. Angle)

- The intelligent system demonstrated a significant reduction in energy consumption compared to conventional methods, thanks to the dynamic allocation of energy based on the actual needs for each steering condition [21].

- The trade–off between SNR and power consumption (SNR-Power Trade-off):

- The analysis demonstrated the system's ability to achieve an effective balance between signal quality and energy efficiency, enhancing its suitability for resource-limited environments.

- Reduced response time by 76% compared to traditional methods, thanks to hardware acceleration and real-time adaptation.

- Reduced energy consumption by 40% due to the use of an intelligent mechanism for distributing energy according to Angular and environmental load.

- Increased signal-to-noise ratio (SNR) by 39%, which enhances the clarity of the connection and its immunity against interference[22].

Vi.Conclusion

This study proposes an intelligent beamforming and capacity optimization system for sixth-generation (6G) networks, implemented on an FPGA architecture and driven by artificial intelligence algorithms. The model showed high efficiency by reducing response time and power consumption with a noticeable improvement in signal quality. The proposed framework has outperformed traditional methods by up to 76% in execution time and 40% in power consumption, which has enhanced the reliability of the link and service by reducing the bit error rate (BER) and the likelihood of outage (Outage), and reducing latency jitter fluctuation under heavy loads. The system also demonstrates strong economic feasibility, thanks to its low implementation cost and the simplicity of the hardware architecture. The adoption of low-consumption, reconfigurable FPGA platforms contributes to reducing long-term operating and energy expenses. In the future, the model will be extended to support MIMO and Rice technologies in real-time, enhancing its capabilities within high-performance adaptive communication environments.

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تشكيل الشعاع التكيفي ومعالجة الإشارات منخفضة الطاقة القائمة على الذكاء الاصطناعي في شبكات الجيل السادس

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الخلاصة:-

مع تصاعد متطلبات شبكات الجيل السادس (6 G) نحو تحقيق سرعات عالية وتحسين كفاءة الطاقة، هناك حاجة متزايدة لحلول تكيفية ذكية وفي الوقت الفعلي داخل طبقة المعالجة المادية. تقترح هذه الدراسة إطارا هندسيا مبتكرا يعتمد على بنية مغلقة تستخدم تقنية الصفيف الكروي الموزع الصغير، المدمجة مع وحدة الذكاء الاصطناعي الداخلية، لتحقيق تشكيل الشعاع التكيفي بكفاءة عالية في البيئات اللاسلكية الكثيفة. الهدف الأساسي من هذا البحث هو تطوير بنية اتصال ذكية تحدد زوايا الإرسال المثلى وتنظم استهلاك الطاقة في الوقت الفعلي من خلال دمج خوارزميات الذكاء الاصطناعي مع تسريع الأجهزة.

المساهمة الرئيسية هي تطوير نموذج عملي يجمع بين الدقة الرياضية والتنفيذ المادي، وذلك باستخدام تصميم طائرات الهليكوبتر القائمة على فبغا وبدعم من محاكاة شاملة داخل بيئة ماتلاب / سيمولينك. أظهرت النتائج التجريبية تحسنا كبيرا في مؤشرات الأداء، بما في ذلك انخفاض بنسبة 42 ٪ في وقت الاستجابة، وانخفاض بنسبة 35 ٪ في استهلاك الطاقة، وتحسن متوسط جودة الإشارة بمقدار 3.8 ديسيبل. تسلط هذه النتائج الضوء على فعالية التصميم المقترح كحل واعد لبناء شبكات اتصالات ذكية وعالية الأداء ومنخفضة الاستهلاك 6 G.

الكلمات الدالة: تشكيل الشعاع التكيفي، شبكات الجيل السادس، تحسين الطاقة، المعالجة في الوقت الحقيقي، الكفاءة الطيفية.