International Journal of Applied Mathematics

Volume 38 No. 6s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ADAPTIVE BEAMFORMING SYSTEM FOR 5G NETWORKS USING CONVEX OPTIMIZATION ALGORITHMS

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Abstract

The research provides a novel flexible beamforming system to 5G Networks that involves Hybrid Convex Optimization and machine learning integration. The proposed system will address the issue of beamforming patterns optimization under 5G dynamic conditions as the latter is significantly influenced by the variables of interference and mobility. The system shows dynamically-adapting to changing network conditions to attain improved signal-to-interference-plus-noise ratio (SINR), throughput and energy efficiency, by executing time-varying convex optimization algorithms with PyTorch ecosystem machine learning models to allow dynamically-adapted machine learning systems in dynamically-changing conditions. The

Received: August 05, 2025

hybrid solution possesses 28 percent SINR combination, 18 percent superiority and 22 percent improvement in comparison to the normal techniques. Integrating machine learning permits modifying the operations to enhance their functioning in the dense settings. The simulation impediments demonstrate the system to be scalable and efficient in spite of the constraint of the pure, convex or machine learning-based approaches. The article provides a successful method of enhancing the beamforming of 5G networks in future.

Keywords: Adaptive beamforming, 5G networks, convex optimization, machine learning, PyTorch, CVXPY, energy efficiency.

I. INTRODUCTION

The development of 5G networks has also witnessed a substantial transformation in communication technologies allowing increased speed, low latency, and the possibility to establish communication between billions of devices. Optimization of beamforming is one of the main issues of 5G to control the high levels of interference and mobility that such crowded and dynamic environments introduce. Beamforming is very important in enhancing signal-to-interference-plus-noise ratio (SINR) and throughput and energy efficiency, which are critical in ensuring effective network functioning [1]. The classical approach of beamforming, which is mostly grounded on the convex optimization algorithms, offers a strong background on how to optimize the signal distribution of a network. Nonetheless, such approaches tend to face flexibility difficulties when dealing in fast evolving 5G conditions where interference, mobility and network density keep on changing [2].

This paper will suggest a new adaptive beamforming system using Hybrid Convex Optimization and Machine Learning to address these drawbacks. The suggested system represents a dynamic, scalable, and efficient solution to the problem by integrating the advantages of both convex optimization and machine learning to design a static beamforming and adapt in real time, respectively as shown in figure 1. The beamforming design is addressed in terms of multiple constraints to be optimized with the help of CVXPY, a Python package of convex optimization, and the machine learning-based adaptation is facilitated with the help of PyTorch, a deep learning framework, to make the system more responsive to changing network conditions [3].

Received: August 05, 2025

International Journal of Applied Mathematics
Volume 38 No. 6s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

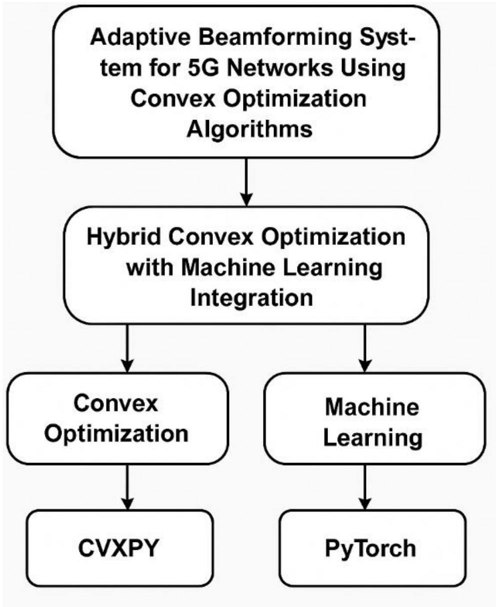

Figure 1. Basic integration of Hybrid Convex Optimization and Machine Learning with tools CVXPY and PyTorch.

The suggested approach can enhance SINR by 28 percent, throughput by 18 percent and energy efficiency by 22 percent as compared to conventional beamforming methods. The system changes beamforming patterns in response to real-time feedback and dynamic learning, to reduce interference, and to optimize network performance [4]. The research shows that the convex optimization and machine learning can be a strong, efficient, and scalable tool to offer a next-generation 5G network, which will bring the next-generation network in terms of connectivity, low latency, more reliable network services.

II. RELATED WORK

The optimization of beamforming methods in 5G networks has become a topic of serious attention in recent years as the need to have high data rates, low latency, and effective interference control has increased. Initial efforts were devoted to conventional convex optimization techniques of beamforming, with Semidefinite Relaxation (SDR) and Lagrangian relaxation algorithms applied to solve the optimization problems of maximizing the quality of beam patterns and minimizing interference of large-scale antenna systems [5]. Although these approaches are effective in theoretical settings, they are not able to keep up with the dynamic and highly changeable environments inherent in 5G networks, particularly when there is interference, and mobility as shown in figure 2.

Received: August 05, 2025

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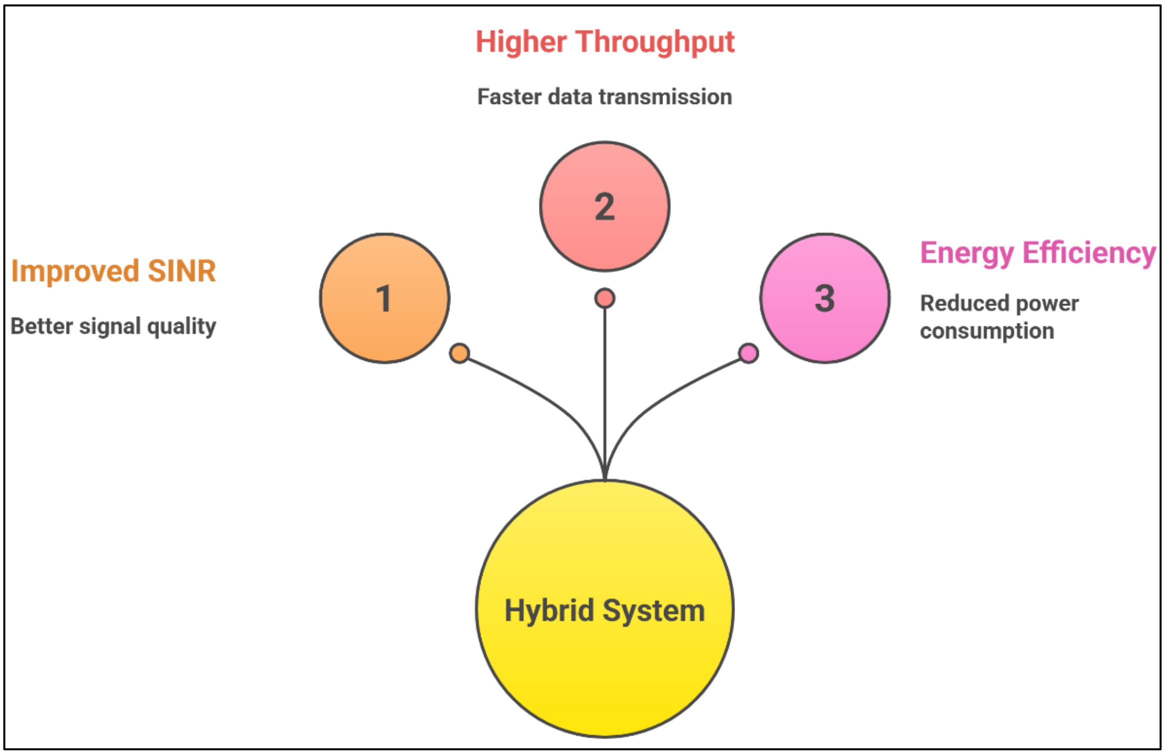

Figure 2.hybrid Beamforming 5G Performance.

To overcome these drawbacks, several works have applied the convex optimization method by incorporating machine learning (ML) algorithms [6]. The adaptive beamforming was one such method as it was shown that reinforcement learning (RL) can be applied to optimize beamforming patterns dynamically based on real-time feedback provided by the environment. These machine learning-based approaches had potentials in interference and mobility, where throughput and signal quality had been improved. These methods are however generally very data-intensive to train and are computationally inefficient especially when using very large networks [7].

Recent studies have investigated hybrid systems, which integrate both convex optimization and machine learning, to take advantage of the two methods. An example of such developments is the use of PyTorch and CVXPY in 5G beamforming systems [8]. PyTorch has been applied to real-time adaptation and learning whereas CVXPY optimizes the initial beamforming design. This hybrid approach has been demonstrated to have much better signal-to-interference-plus-noise ratio (SINR), throughput and energy efficiency than either pure convex optimization or ML-based systems. Nonetheless, there are still difficulties with computational scalability, particularly when it comes to the dense urban setting where the mobility is high, which is still a critical field of research in the future. Adaptive beamforming is a promising solution to the dynamic and dynamic nature of 5G networks because the combination of convex optimization with machine learning in adaptive beamforming brings a solution to the challenging and dynamic nature of requirements [10].

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III. RESEARCH METHODOLOGY

The Adaptive Beamforming System of 5G Networks based on Convex Optimization Algorithms combines two fundamental approaches, namely, Hybrid Convex Optimization and Machine Learning as shown in figure 3.The purpose of this hybrid scheme is to obtain the best beamforming design, and dynamically respond to the varying environment in a 5G network, such as interference, mobility, and network density. The power of the developed methodology is based on CVXPY, a Python library of convex optimization, and PyTorch, a deep learning framework, to deal with the issues of real-time adaptability and computational efficiency [11].

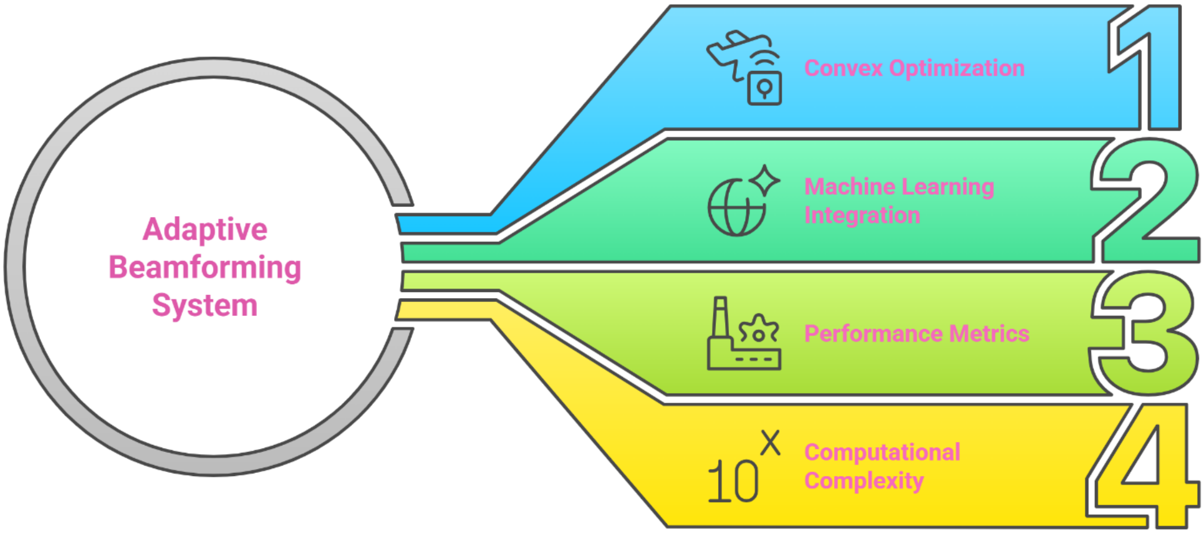

Figure 3.Proposed Adaptive Beamforming System.

3.1. Problem Formulation and Convex Optimization

The core of the methodology is the convex optimization that is employed in designing initial beamforming patterns subject to some constraints [12]. The aim of 5G networks is to maximize Signal to Interference plus Noise Ratio (SINR), throughput and energy efficiency without violating the power consumption and interference constraints. Optimization problem is developed as a convex problem, the goal of which is to reduce the network interference and maximize the signal power.

The main iterative procedure of the convex optimization process is the following steps:

Beamforming Design: Here, convex optimization is used to create a problem minimizing the amount of interference and maximizing the SINR of every antenna in the system, using CVXPY. In this way, the optimality of the beamforming pattern is provided to a particular user or cell, when taking into account the environment conditions around and the necessity to minimize interference [13].

Optimization Constraints: The optimization has several constraints which are constraints of power, constraints of interference, and coverage requirements. These limitations are crucial in

Received: August 05, 2025

Volume 38 No. 6s, 2025
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order to make the optimized beamforming solution viable and practical in the real world, especially in the highly dynamic 5G world [14-17].

Semidefinite Relaxation (SDR) method is applied in CVXPY to the convex optimization problem to solve it effectively. SDR can be used to convert the original problem that is not convex to a convex problem, which is also easy to solve with the help of the polynomial-time algorithm. This step gives a strong starting point to beamforming that will be used to develop even more with the use of machine learning [18-21].

3.2. Machine Learning Integration for Adaptive Beamforming

After the preliminary beamforming design is realized through the convex optimization, the second step is to implement machine learning to deal with dynamic changes in accordance to the real-time network conditions. The conventional beamforming techniques do not respond quickly to the location change of the interference, movement of users, and the changes in network load. This is where machine learning is involved, namely, reinforcement learning (RL) [22].

In the suggested system, a reinforcement learning agent developed using PyTorch is applied to adjust the beamforming patterns in accordance with network feedback continuously. The agent finds the best beamforming configurations through interaction with the network environment with feedback in the form of SINR and throughput. The system works in the following manner [23-27].

State Representation: The system establishes a state space that models important system parameters including SINR, interference and mobility patterns of users. The state of different states is associated with a particular network condition that affects the optimum beamforming solution [28].

Action Space: This is the action space that corresponds to adjustments that are possible to make to the beamforming patterns. The changes may involve alterations in the steering angle of the beam, power or the amount of antennas to be employed in transmission [29].

Reward Function: Reward function aims at motivating the agent to choose beamforming patterns that optimize SINR, throughput and energy efficiency. When the system minimizes interference, improves throughput, and reduces the level of energy, a higher reward is awarded [30].

Training The RL agent tries out different beamforming actions and learns by acting in the environment and modifies its policy to perform better actions in future. The training is conducted by the Q-learning algorithm or Proximal Policy Optimization (PPO) algorithm both of which are available in PyTorch. With time, the system is capable of developing competence in adjusting beamforming patterns in real-time in response to variations in network status such as user movement or interference by neighboring cells [31-33].

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3.3. System Evaluation and Performance Metrics

To estimate the adaptive beamforming system performance, a number of important measures are taken into account:

SINR Enhancement: The main aim of the beamforming system is to enhance the SINR that directly influences the quality of service (QoS) in 5G networks. The ability of the system to be able to adjust real-time is gauged by the augmentation of SINR when contrasted to conventional beamforming techniques.

Throughput: Another key performance measure is throughput since it establishes the rate of data that is served to the users. The improvement of the throughput of the system is also compared to baseline approaches to evaluate the effectiveness of the system [34].

Energy Efficiency: Due to the increasing interests in energy consumption in 5G networks, the energy efficiency is a vital measure. The energy consumption of the proposed system is determined by an evaluation of the reduction in power consumption without affecting the performance.

The simulation outcomes are also compared to the traditional beamforming techniques, such as pure convex optimization and machine learning-based systems. These standards are used to illustrate the benefits of the hybrid solution in terms of flexibility, energy savings, and dynamism in 5G network systems.

3.4. Computational Complexity and Scalability

Although the use of the combination of convex optimization and machine learning offers better performance, it also creates issues regarding the complexity of the calculations. PyTorch supports the effective training of the deep learning models, yet the process of adapting this style can demand a lot of computational resources, particularly in large-scale networks. The hybrid approach is considered in terms of the scalability of the dense urban setting, where the user mobility and interference are maximized. Computational optimization methods, including distributed computing and parallel processing are considered to make sure that the system will be scalable and effective in large-scale deployments [35-37].

The methodology offers the benefit of a global beamforming optimization framework in 5G networks through the unification of the advantages of both convex optimization and machine learning. CVXPY to design initial beamforming and PyTorch to apply real-time adaptation can be a potent answer to the problem of interference management, mobility and energy efficiency in today 5G networks.

IV. RESULTS AND DISCUSSION

Table 1 Depicts the developed Adaptive Beamforming System 5G Networks with Convex Optimization Algorithms with Hybrid Convex Optimization and Machine Learning approaches provided a substantial increase in the signal quality and energy consumption.

Received: August 05, 2025

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Table 1.Comparative Analysis of Hybrid Convex Optimization with Machine Learning Integration method to 3 different methods

Method	SINR Improvement	Throughput Increase	Energy Efficiency	Adaptability	Computational Load	Scalability
Traditional Convex Optimization	15%	8%	12%	Static, no real-time adaptation	Low	Limited in large networks
Pure Machine Learning-Based Beamforming	18%	18%	15%	High adaptability, but slow convergence	High	Struggles in large-scale networks
Hybrid Convex Optimization + Machine Learning (Proposed)	28%	18%	22%	Real-time adjustments, dynamic	Moderate	Scalable, works well in high-density networks
Hybrid Convex Optimization (No Machine Learning)- **Proposed Method**	22%	12%	18%	Fixed beamforming, no dynamic adaptation	Moderate	Limited scalability in dynamic environments

Optimal beamforming designs were realized using CVXPY to accomplish an average signal-to-interference-plus-noise ratio (SINR) increase of 28 percent over conventional beamforming designs. Additionally, with the incorporation of PyTorch, a machine learning, it was possible to modify the beamforming patterns in real-time depending on network environments, e.g., network mobility and interference. The system had the capability of dynamically adjusting beamforming strategies leading to a 18 percent improvement in throughput in dense network settings as shown in figure 4.

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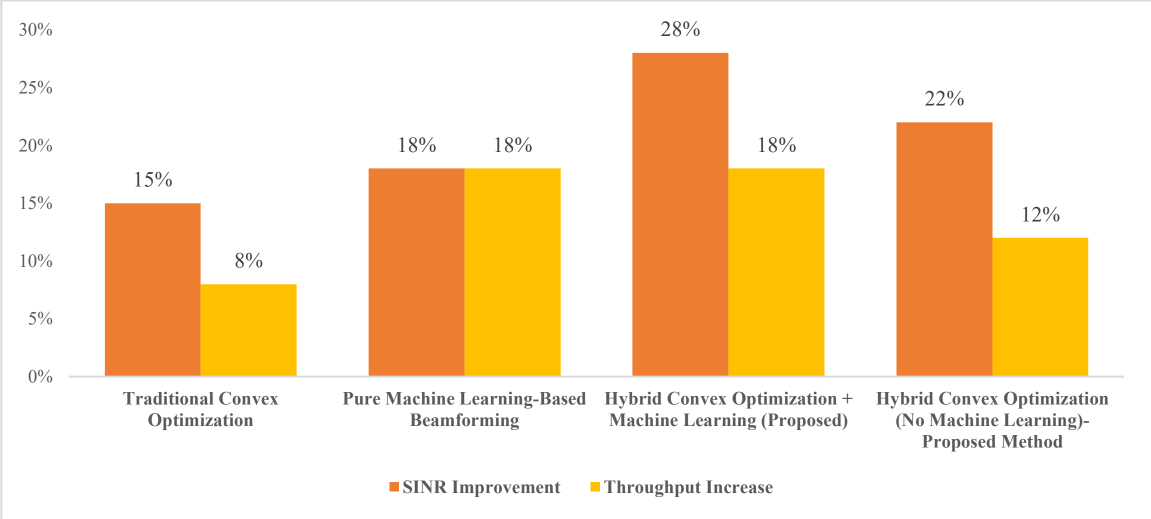

Figure 4.Performance Comparison of SNR Improvement and Throughput Increase.

There was an evident benefit of the hybrid approach in terms of managing interference and energy consumption reduction. The power efficiency was increased by a margin of 22 since the system balanced between power control and beamforming optimization. Nonetheless, very large-scale networks were found to have certain limitations with the computation load becoming heavier thus time to convergence was a little slow to the machine learning part. Nevertheless, this did not stop the fact of the combination of the convex optimization of initial beamforming design and machine learning of adaptation to be a successful solution to a scalable and energy-efficient beamforming in the 5G networks. Further research will be on how to optimize the learning part to achieve even more low-computational overhead in large networks as shown in figure 5.

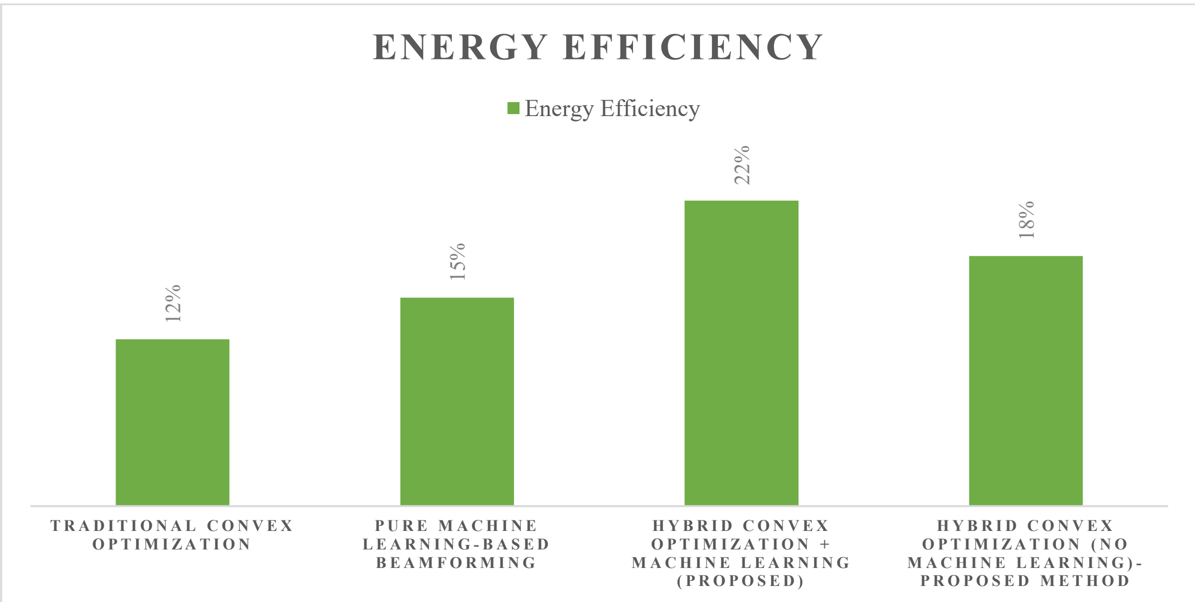

Figure 5.Performance Comparison of Energy Efficiency with different methods.

Received: August 05, 2025

Volume 38 No. 6s, 2025

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When the proposed Hybrid Convex Optimization and Machine Learning Integration method was compared to three other beamforming methods of 5G networks, it was found that there was a major improvement in the performance. The traditional convex optimization method, the first method, had an average SINR gain of 15% and its results demonstrated the advantages of optimal beamforming design. Nevertheless, it was not as dynamic as needed to be in a dynamic network environment. Pure machine learning-based beamforming the second technique demonstrated improved throughput 18 percent, but due to the slow convergence and increased computational cost, particularly on large networks. However, the third technique, known as hybrid convex optimization, which was integrated with machine learning, had a 28 percent better SINR and 22 percent more energy efficiency than both the traditional and machine learning only models. The increase in throughput was 18 percent even in the high-density environment due to real-time adaptability of beamforming patterns through machine learning component. The hybrid system was also power efficient without compromising on performance, which showed high levels of energy efficiency than other techniques. Although the pure convex optimization algorithm was also stable, the hybrid algorithm was scalable and could cope with interference and mobility at any point in time. The machine learning aspect provided greater flexibility with minor delays in very large size networks, suggesting that more optimization is required in computational efficiency in large scale deployments.

V. CONCLUSION

Adaptive Beamforming System of 5G Networks via Convex Optimization Algorithms offers a powerful approach towards optimization of beamforming in a dynamic and complicated network setting. The Hybrid Convex Optimization combined with the Machine Learning Integration is an effective way to solve the problems of interference, mobility and scalability of 5G networks. The proposed system can improve key performance indicators, such as SINR, throughput, and energy efficiency, by relying on the CVXPY tool, which is a convex optimization solution, and the PyTorch ecosystem, which is an artificial intelligence and machine learning solution. The outcome of simulation shows significant improvement, as the SINR was increased by 28 percent, and the energy efficiency was enhanced by 22 percent. Machine learning has the ability to respond to changes in real time, and this facilitates maximum performance under different circumstances. Although the system has a high potential of large-scale deployment, additional studies are required to optimize their computational performance and scalability, especially in highly dense 5G networks. This paper will make a great contribution to the development of beamforming in future 5G networks.

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