Performance Investigation Of 5G Beyond Network

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As communication networks transition from 4G to 5G and look ahead to the prospects of 6G, the demand for improved performance, reduced latency, and enhanced reliability becomes increasingly pronounced. This report delves into the dynamic landscape of modern communication networks, exploring the challenges and opportunities brought by the evolution to 5G and the anticipated horizons of 6G. In response to these challenges, a novel approach is proposed the integration of Machine Learning (ML) for intelligent path ranking within communication networks. Path ranking, a crucial element in resource allocation and network efficiency, is at the heart of this approach. The proposed work leverages ML's capabilities to adaptively rank communication paths in real-time, empowering networks to dynamically respond to changing conditions. Through rigorous evaluation across key performance parameters, including throughput, delay, loss probability, and computational overhead, this report demonstrates the consistent superiority of the ML-driven path ranking approach over scenarios without such ranking. For instance, in scenarios involving 100 nodes, the proposed system achieved a remarkable throughput improvement of approximately 13.2%, showcasing the substantial impact of path ranking on resource optimization. Furthermore, it significantly reduced network delay (approximately 14.4%) and lowered loss probability by approximately 6%, underlining its efficacy in enhancing network reliability and data integrity. The integration of ML-driven path ranking offers a concrete solution to the evolving challenges posed by 5G and the envisioned horizons of 6G. This report emphasizes the pivotal role of path ranking in network optimization, providing a foundation for continued research and development in the exploration of ML and AI techniques to further enhance communication networks. As networks continue to evolve, the path ranking approach presents a path towards adaptive and intelligent communication infrastructures capable of meeting and exceeding the demands of future applications and services.

Keywords: 5G beyond, Machine learning, Quality of Service, Throughput.

1 Introduction

Regardless of the way that 5G is as yet in the fundamental stage of business scale as it deployed worldwide. It is also mandatory for us to simultaneously know about the communication needs of the future society. In the world of Technology, where the speed of the network is the most important parameter of concern, internet users somewhere face the problem of low speed due to traffic. Present 5G network technologies are not capable of delivering the extreme data-rates, extreme reliability, extreme-availability, extreme low-delays and massive scalability demanded by emerging technologies like XR Technologies, N-Iot etc. Existing 5G networks are also not designed to handle unique security vulnerabilities such as paging occasion and stingrays in UAV Applications. Users need an instant and efficient System. N-Iot uses mainly molecular communication which seems difficult to enable by 5G.Nano networks uses terahertz band for better performance which is not possible in 5G technology.

The forthcoming 6G era will be defined by a seamless integration of Machine Learning (ML), Artificial Intelligence (AI), Deep Learning, Data Science, Data Analytics, and Data Mining, forming the bedrock of this advanced wireless technology. These intertwined disciplines will collectively spearhead the evolution of networks, services, and user experiences, redefining the boundaries of what's possible in the digital realm. Advanced ML and AI will stand as the cornerstone of 6G, ushering in a new era of adaptability and intelligence. Networks empowered by these technologies will possess dynamic learning capabilities, enabling them to forecast demands, adapt in real time, and optimize resources efficiently. The predictive prowess of ML will predict network behaviors and user preferences, facilitating proactive adjustments and personalized services. Deep Learning, a subset of ML, will play a pivotal role in processing the massive volumes of data generated by 6G networks. Its ability to recognize intricate patterns within data streams will empower networks to glean invaluable insights, supporting decision-making processes and enabling networks to tackle complex problems with unparalleled efficiency. Additionally, neural networks will drive significant strides in automation, facilitating self-optimizing networks that continuously evolve and adapt without direct human intervention.

The chapter traces the evolution from 1G to the groundbreaking impact of 5G while peering into the speculative realm of 6G. It explores 5G's performance metrics, emphasizing its extensive influence beyond traditional networks, and details enabling technologies like Massive MIMO, millimeter-wave spectrum, and network slicing pivotal in 5G's expansion. Anticipating the future, the chapter envisions 6G's transformative potential, highlighting AI, ML, and quantum principles as driving forces. It outlines 6G's anticipated advancements, from terahertz frequencies to holographic communications, setting the stage for revolutionary connectivity. However, the realization of these advancements relies on ongoing research, collaborations, and technological breakthroughs, shaping a future where innovation redefines connectivity and technological boundaries.

2 Literature Review

The existing work of various Researchers focusing of different areas of network. To achieve this, several published articles have been surveyed to analyze the current status of technical advances to meet the demands of present-day multimedia services and applications that required high-quality data transfer. Some Researchers motivate the need to move to a sixth generation (6G) of mobile communication networks, starting from a gap analysis of 5G and integration of ML and AI to Optimize Network.

The Research Activities related to that 5G is unable to meet the requirements and advancements were presented by **Elmeadawy & Shubair (2019)** identified 5G limitations in accommodating diverse technologies; Explored potential enhancements with 6G networks for improved QoS and technology integration [1].**Mourad et al. (2020)** outlined a foundational roadmap for the progression of 5G new radio across short-term (2022), medium-term (2025), and long-term (2030) timescales. The authors aimed to spark discussions within the wireless research community, seeking feedback for future refinements as the evolution of 5G unfolds [2].**Khan et al. (2020)** Explored technological advancements and challenges towards 6G wireless systems encompassing machine learning, communication, networking, and computing; Proposed practical solutions for AI- driven transceivers, energy harvesting, secure business models, cell-less architecture, and distributed security[3]. for **6GBorole et al. (2020)** Emphasized the urgency for technological enhancement in the internet sector; Proposed NCC mechanism, network slicing, and 6G implementation to improve speed and mitigate signal attenuation issues[4].**J.kaur et al. (2021)** highlights the vital role of ML across all network layers, enhancing efficiency in 6G systems. Unsupervised learning, especially K-means, is emphasized for optimizing resource allocation and managing dense wireless networks[5]. **W. Jiang et al. (2021)** notes that most prior 6G research focused on isolated aspects like THz, AI, or ML, lacking a holistic view. It identifies a gap in comprehensive assessments covering drivers, scenarios, and technologies[6]. **Sharma et al. (2021)**Explored the evolving role of optical and wireless technologies and emphasizes future needs for AI-driven optimization and innovative strategies to support ultra-low latency, high bandwidth, and diverse 6G services. [7]. **Khan et al.(2022)** Proposed congestion control mechanism integrating deep learning achieved high accuracy under diverse network conditions, essential for optimizing performance in 5G/6G networks [8].

3 Proposed Methodology

The proposed work in this section is dedicated to the primary objective of significantly enhancing the resource utilization in 5G and beyond wireless networks, the efficient allocation and management of network resources remain a pressing challenge. To address this, we are utilizing a set of key parameters encapsulated within the 'parameter_list' structure. The deployment and the resource provisioning our proposed work focuses on efficient resource provisioning within the IoT layer, where diverse users demand resources that can be provided by other network users. We aim to create a network environment that allocates resources through dedicated paths from source to destination, balancing minimal transmission delay and maximum resource efficacy. This framework optimizes resource allocation across the IoT layer, crucial for the dynamic and interconnected nature of IoT devices and sensors. By enhancing resource utilization, our approach ensures efficient communication for various IoT applications and services, considering random user deployment within a specified range.

Firstly, the proposed work initializes several key parameters, such as 'UE_count,' 'move_speed,' 'storage_capacity,' and others, to configure the network's characteristics. The 'UE_count' represents the number of User Equipment (UE) in the network, and these UEs are randomly deployed within a 500x500 unit area. Next, the proposed work calculates the distances between all pairs of UEs using a nested loop that computes the Euclidean distance between each pair based on their coordinates. These distances are stored in the 'node_distance' matrix, which is a crucial factor in signal propagation and interference within the network. The proposed work then proceeds to simulate resource allocation scenarios by varying the computational load on the UEs. For each load level, a list of devices ('device_list') with random input sizes, computation requirements, and storage demands is created as Shown in Figure 1. These devices will seek resources from the network. To allocate resources efficiently, a path is constructed from source to destination for each device as shown in Figure 2, prioritizing a balance between minimizing transmission delay and maximizing resource efficiency.

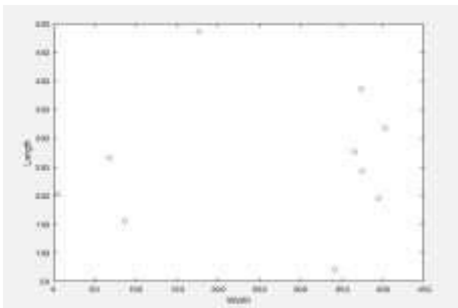

Figure1: User Deployment

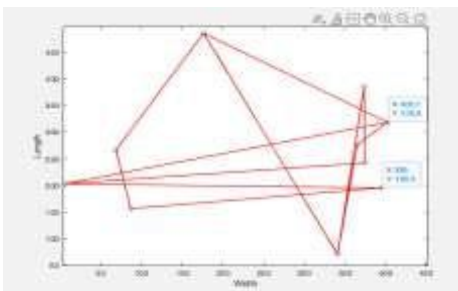

Figure2: Constructed path from source to terminal end

Resource allocation and path determination are performed using the 'PSTopLayer' function, which takes into account the device list and network parameters. After each resource allocation iteration, the proposed work records various performance metrics, such as completion time, end-to-end delay, and resource utilization. It also calculates total losses considering packet loss probabilities and measures the time taken for resource allocation. The recorded data allows the proposed work to analyze the network's efficiency under different load conditions and resource allocation strategies. In addition, the proposed work performs a similar set of resource allocation simulations using an alternative method ('PSTopLayerAI') and records corresponding performance metrics for comparison. These two methodologies enable the proposed work to evaluate the effectiveness of different resource allocation strategies within the network.

To evaluate and improve the current network context, several key performance metrics have been computed. These metrics provide insights into the efficiency and effectiveness of the resource allocation and scheduling processes. The parameters involved in this evaluation include:

Throughput, Average Delay, Path Losses, Average Utilization

The evaluation of these parameters provides a comprehensive understanding of the network's performance, resource allocation effectiveness, and the impact of the path planning and computation scheduling algorithm. By analyzing and improving throughput, average delay, path losses, and average utilization, the network can enhance its overall efficiency, reduce latency, and optimize resource utilization, thereby meeting the evolving demands of modern communication systems. The aggregated parameters, encompassing key network performance metrics, play a pivotal role in assessing the quality and efficiency of communication paths. These metrics provide a holistic view of how effectively resources are allocated and utilized within the network. However, to make informed decisions about resource allocation and path selection, it is essential to categorize these paths into distinct quality groups.

To achieve this categorization, the K-Means clustering algorithm is employed. K-Means is an unsupervised machine learning technique that partitions data points into clusters based on their similarity. In this context, paths exhibiting similar performance characteristics are grouped together into clusters representing different path quality levels. For instance, paths with high throughput, low delay, minimal losses, and high utilization may fall into the "good" cluster, while those with intermediate performance metrics may be classified as "moderate," and paths with poor performance may be categorized as "bad." Once the paths have been clustered into these quality groups, they serve as the training dataset for a Multilayer Neural Network. The neural network is designed to learn and internalize the relationships between the aggregated parameters and the associated path quality levels. Through a training process, the neural network becomes adept at classifying new, unseen paths into one of these predefined categories. It effectively becomes a decision-making model that can assign a quality label (good, moderate, or bad) to any given communication path based on its performance metrics.

The classification scores produced by the trained Multilayer Neural Network serve as valuable indicators of path quality. Paths with higher classification scores are deemed of superior quality and are prioritized for utilization in data transmission and communication tasks. Conversely, paths with lower scores may be considered for less critical or lower-priority tasks. This ranking mechanism enhances the efficiency of path selection within the network.

The architecture can be explained using the following algorithmic architecture.

Algorithm 1 Path Quality Categorization using K-Means and Neural Network

Input: Aggregated Parameters (Throughput, Avg_Delay, Path_Losses, Avg_Utilization)
Output: Path Quality Category (Good, Moderate, Bad)
Initialize k (number of clusters) and perform K-Means clustering:
  $X \leftarrow$ Concatenated parameters
  $C \leftarrow$ Initial cluster centroids
  Repeat until convergence:
    Assign each path to the nearest centroid using:
      $\text{Cluster}(x_i) = \arg\min_{c_j} \|x_i - c_j\|$
    Update cluster centroids:
      $c_j = \frac{1}{\text{ClusterSize}(j)} \sum_{i=1}^{n} x_i$, for $j = 1, 2, ..., k$
Train a Multilayer Neural Network for path quality classification:
  Define training data ($\boldsymbol{X}$) and labels ($\boldsymbol{Y}$)
  Define the neural network architecture with parameters $\boldsymbol{W}$ and $\boldsymbol{b}$
  Initialize weights and biases: $\boldsymbol{W}^{(l)}$ and $\boldsymbol{b}^{(l)}$ for layer l
  Repeat until convergence:
    Forward propagation: Compute activations ($\boldsymbol{A}^{(l)}$) using weights and biases:
      $\boldsymbol{Z}^{(l)} = \boldsymbol{W}^{(l)}\boldsymbol{A}^{(l-1)} + \boldsymbol{b}^{(l)}$
      $\boldsymbol{A}^{(l)} = \sigma(\boldsymbol{Z}^{(l)})$ (where σ is an activation function)
    Calculate the cost function (J) using predicted labels ($\hat{\boldsymbol{Y}}$) and actual labels ($\boldsymbol{Y}$):
      $J(\boldsymbol{W}, \boldsymbol{b}) = -\frac{1}{m}\sum_{i=1}^{m}\left(\boldsymbol{Y}_i \log(\hat{\boldsymbol{Y}}_i) + (1 - \boldsymbol{Y}_i)\log(1 - \hat{\boldsymbol{Y}}_i)\right)$
    Backpropagation: Update weights and biases to minimize J using gradient descent:
      $\boldsymbol{W}^{(l)} \leftarrow \boldsymbol{W}^{(l)} - \alpha\frac{\partial J}{\partial \boldsymbol{W}^{(l)}}$, $\quad \boldsymbol{b}^{(l)} \leftarrow \boldsymbol{b}^{(l)} - \alpha\frac{\partial J}{\partial \boldsymbol{b}^{(l)}}$, for all layers l
  Use the trained network to predict the path quality category based on the output layer activation $\boldsymbol{A}^{(L)}$
Return: Path Quality Category

Table1: Multilayer Neural Network Training

Overall, the integration of machine learning techniques, including K-Means clustering and a Multilayer Neural Network, into the network's decision-making process significantly enhances its ability to allocate resources efficiently and select optimal communication paths. This, in turn, leads to improved network performance, reduced latency, and optimized resource utilization,

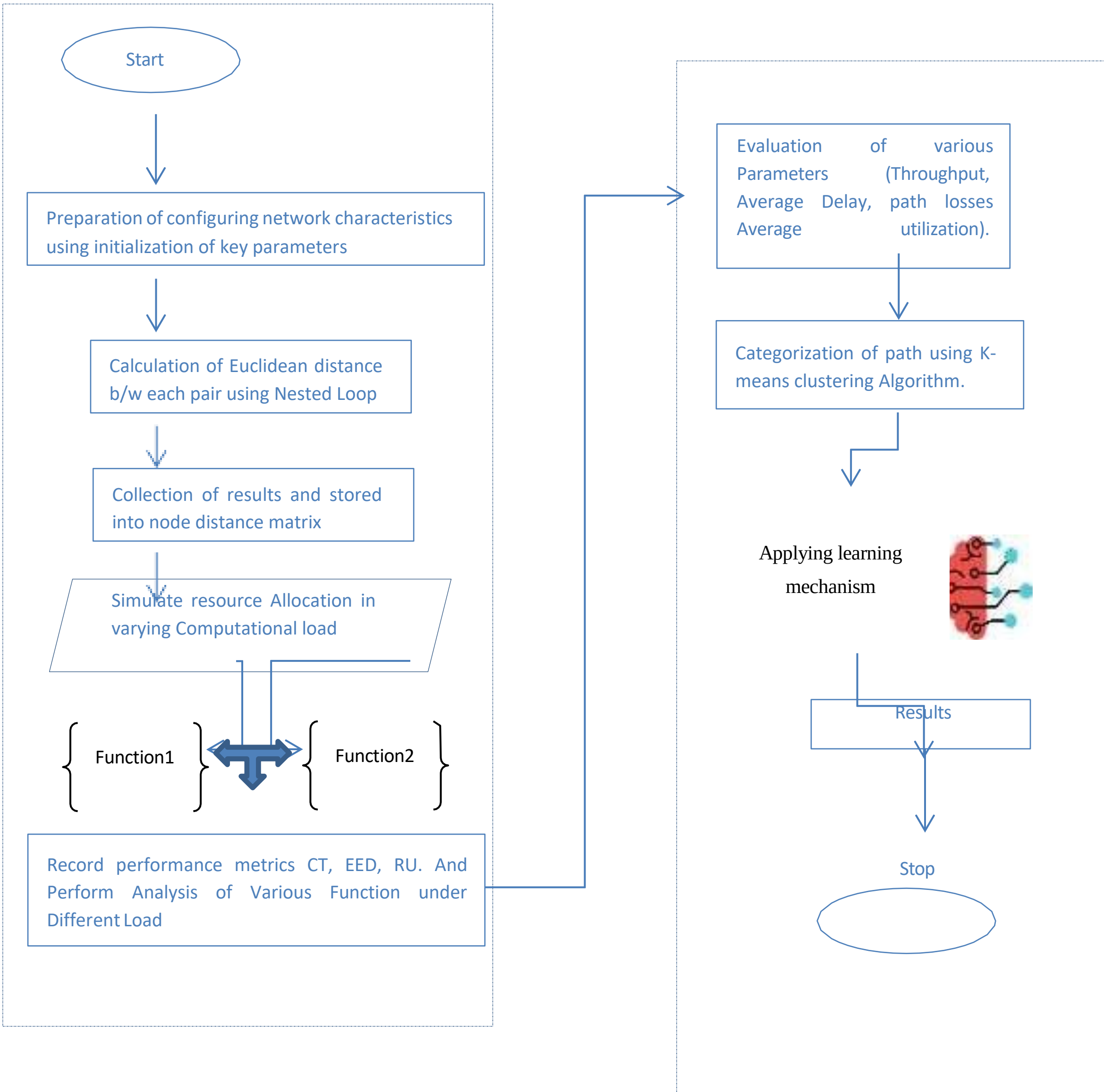

Figure 3: Workflow process of the proposed methodology

aligning the network with the evolving demands of modern communication systems. The generated rank helps in selecting the next UE for the selection to optimize the overall resource utilization and to reduce the overall latency at the same time.

4 Results and Discussion

The proposed work has undergone a comprehensive evaluation process to assess its performance across various key parameters, including overall latency (or delay), throughput, path loss probability. This evaluation was conducted across different scenarios involving a varying number of nodes ranging from 50 to 100, with increments of 10 nodes, for a total of 100 iterations in each scenario. This extensive evaluation approach allowed for a thorough analysis of the network's performance under varying node densities and loads. It enables network administrators and researchers to make informed decisions to enhance the overall efficiency and reliability of the communication system.

The presented table offers valuable insights into the performance of the proposed communication system, highlighting the significant impact of path ranking on optimizing network throughput across various scenarios characterized by different numbers of User Equipment (UE) devices.

As the number of UE devices increases from 50 to 100, the proposed path ranking mechanism consistently improves network throughput. The difference is minimal at lower densities but becomes more significant as network size grows, demonstrating the system's efficiency in managing larger networks.

'No of UE'	'Throughput Proposed'	‘Throughput without Ranking’
50	310.198915	294.391789
60	310.406106	281.696697
;70	342.477558	319.112053
80	480.767809	415.059999
90	513.004796	450.694829
100	697.043017	615.872474

Table 1: Performance Analysis in terms of Throughput

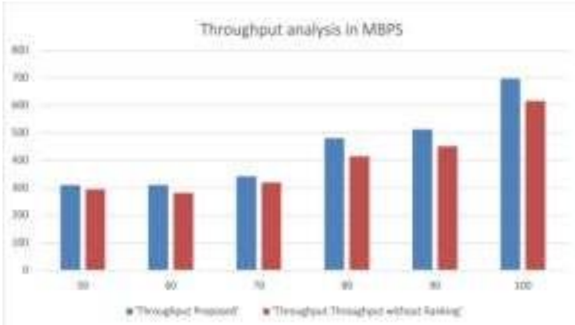

Figure 4: Graphical Illustration of Throughput Analysis

'No of nodes'	'Loss Probability Proposed'	'Loss Probability withoutranking'
50	0.21844392	0.23349307
60	0.22614552	0.24073063
70	0.23352979	0.24487231
80	0.23997422	0.27105652
90	0.24659366	0.28458317
100	0.24924145	0.2650969

Table 2: Performance Analysis in terms of Path loss probability

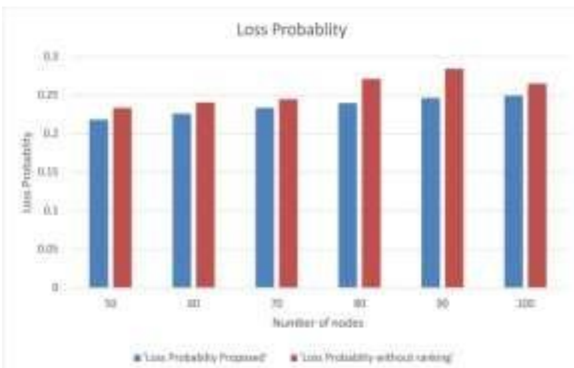

Figure 5: Graphical Illustration of Path Loss Probability Analysis

'No of nodes'	'Delay Proposed'	'Delay without ranking'
50	10.2014594	11.430063
60	11.2743414	11.6709151
70	34.2393419	35.5312743
80	62.5945653	65.2102034
90	75.079323	87.7216172
100	94.4458793	103.502544

Table 3: Performance Analysis in terms of Latency.

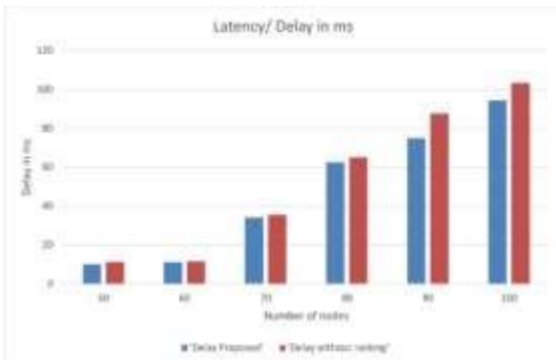

Figure 6: Graphical Illustration of Latency Analysis

5 Conclusion and Future scope

In the ever-evolving landscape of communication networks, the transition from 4G to 5G marked a significant paradigm shift. The advent of 5G networks brought forth a multitude of transformative features, from ultra-low latency and gigabit-level data rates to the ability to accommodate massive device connectivity. The sheer diversity of use cases in 5G networks demands efficient resource allocation and dynamic path selection to ensure optimal network performance. As the world anticipates the arrival of 6G networks around 2030, the vision extends even further, encompassing concepts like holographic communication, advanced AI integration, and ubiquitous connectivity. The journey towards 6G presents exciting opportunities but also magnifies the complexities in managing intricate and densely populated networks.

In proposed work, the path ranking approach represents a pivotal step towards optimizing communication networks in the 5G era and beyond. The integration of ML-driven path ranking offers tangible benefits in terms of throughput, delay, loss probability, and network efficiency.

With 100 nodes, the proposed system achieved a remarkable throughput of 697.043017 Mbps, whereas the scenario without ranking achieved 615.872474 Mbps. This represents a substantial improvement of approximately 81.170543 Mbps (about 13.2%) achieved. the proposed system achieved a notably lower delay of 75.07932302 ns compared to the scenario without ranking, which resulted in a delay of 87.72161718 ns. This represents a substantial reduction in delay of approximately 12.64229416 ns (about 14.4%) achieved by the proposed system. the proposed system achieved a loss probability of 0.249241453, whereas the scenario without ranking resulted in a loss probability of 0.265096902. This represents an impressive reduction in loss probability by approximately 6% . The computational overhead introduced by the path ranking mechanism is a crucial aspect to consider. It represents the additional computational resources required to implement and maintain.

The ML-driven path ranking system While there is an inherent computational cost associated with ML integration, the benefits in terms of network optimization and performance enhancement outweigh the overhead. The evaluations showcased that the proposed system effectively managed computational resources while delivering substantial improvements in network metrics.

As 6G networks loom on the horizon with their promise of even more transformative capabilities, the adaptability and intelligence of such systems will become increasingly crucial. The path forward involves continuous research and development to harness the full potential of ML and AI in network optimization while addressing security concerns. By doing so, the communication networks can meet and exceed the demands of the future, enabling groundbreaking applications and services that shape our connected world.

6 References

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