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THE DARK SIDE OF AI IN TELECOM: ADDRESSING BIAS IN NETWORK OPTIMISATION MODELS

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Abstract:

The dynamic development of 5G and future 6G networks has turned AI-driven resource allocation into a pillar of effective telecom operation. Nevertheless, fairness and transparency in these AI systems are largely unexamined. The research introduces a thematic analysis method to detect algorithmic disparity and injustice in resource distribution among various Quality of Service (QoS) classes. As a novelty, this analysis runs on a qualitative telecom dataset with parameters such as throughput, latency, and packet loss categorised by QoS levels High, Medium, and Low. The approach incorporates the six-stage thematic analysis scheme, tailored for numerical data interpretation. To develop the model, codes were pulled from trends affecting throughput, latency, and the number of packets lost among different QoS groups. The main ideas were used to enhance the AI resource scheduling model to check that the method worked. Based on the results, there was a clear pattern of high-priority services receiving better throughput, lower latency, and fewer packet losses compared to the lagging and compromised services for the medium and low-tier categories. As a result, the fairness in resource allocation improved by 9.6%, as shown by a steady throughput across all QoS classes and a noticeable reduction in the difference between the latencies of different classes. The study highlights how qualitative thematic findings can be incorporated into AI optimisation, making the process more equitable. The findings help ensure AI is used fairly and ethically in future telecom networks.

Key Words: Algorithmic Bias, Fairness Metrics, Network Optimisation, Quality of Service, Resource Allocation, Thematic Analysis

1. Introduction:

In the era of 5G and 6G telecoms, Artificial Intelligence is really important to help make sure future wireless networks can handle many different tasks without getting too complicated (Iosup et al., 2022, p. 28). Perhaps the biggest improvement in this area is AI-based network slicing, which makes network providers split up the network and give resources to different services according to needs and importance. This ability is important as telecommunication networks start supporting various services from low-latency to high-speed learning. Perhaps the most important development in this field is AI-facilitated network slicing, which lets network operators change how they share resources based on which types of service and which users need them the most. This ability is important as today's networks have to support many different kinds of things, whichmust be fast or large files used in education.Yet, as AI takes more responsibility for such resource allocation choices, there are apprehensions about its transparency, fairness, and propensity to amplify existing disparities. Specifically, the issue of whether AI models distribute network resources fairly between different QoS classes and traffic types remains broadly untapped (Raghavendar et al., 2023, p. 8). As digital infrastructure becomes central to social engagement, discriminatory AI behaviour within telecom networks can inadvertently exclude specific user groups, thus producing far-reaching ethical and practical concerns.

Prior research on AI in telecommunications has tended to optimise performance metrics like latency minimisation, throughput optimisation,and network efficiency by applying supervised learning, reinforcement learning, and optimisation algorithms (Ramagundam, 2023, p. 438). Although technically sound, these studies typically view fairness and bias as secondary concerns or infer neutrality in data and model behaviour. Additionally, Qualitative approaches in these analyses might fail to capture contextual inequalities or nuanced discrimination built into AI decision-making. Fewstudies evaluate critically how AI models prioritise or deprioritise service classes under different network conditions. Such a gap is critical in network slicing situations, where resource allocation decisions are autonomously and dynamically performed. Absence of a critical analysis of these patterns can cause AI systems to reinforce structural unfairness, particularly in high-traffic situations where compromises become imminent. The lack of fairness-oriented assessments makes it hard to ensure everyone gets fair access to digital services, especially when it comes to less important things or those that matter most to society.

The research fills this space by using interviews and surveys to examine what biases the AI shows when deciding how to split up the network. Leveraging the Wireless Network Slicing Dataset, which simulates real 5G/6G networks, the study uses a thematic approach to find patterns in how AI plans out resources in mobile networks. The data set has important info like how busy a network is, the type of internet activity, how important it is, how fast the connection is, and whether any data gets lost, all of which help check how fair different services get treated. The process includes fixing data, finding outlierslike throughput and latency into simple parts, and grouping things people notice, like way AI splits up resources and how stuck it can get with certain tasks.By analysing these trends regarding fairness, the research sheds light on how AI may prioritise top-grade services and exclude others, such as educational or low-priority applications. The findings add to the general debate on ensuring responsible deployment of AI in telecom, calling for transparency, inclusivity, and ethical regulation in future networks.

2. Literature Review:

Alabi (2023, p. 1) introduces that networks can do real-time optimisation thanks to the intelligent decisions theycan make. Unlike static ones, AI systems can predict the behaviour of networks and change traffic management based on machine learning. Thanks to these solutions, operator expenses go down because resources are used efficiently and energy is saved. Fault detection is improved by AI, which spots anomalies early and takes action to keep services running smoothly. As 5G and IoT integration grow, AI keeps telecom networks more secure by detecting and blocking threats immediately. AI makes it possible to provide more tailored services by studying how people use the network. Using AI generally makes telecom networks more responsive, trustworthy, and focused on end-users.

Rana et al. (2022, p. 1) suggest that businesses usually believe introducing AI-BA will help them get a head start over their competitors. However, current research is showing that AI-BA has some undesired negative effects. A lack of clear AI-BA rules, untrusted data, and inadequate workforce training can generate problems for decision-making. A lack of transparency can make it difficult for businesses to make the right choices and increase employee risk. As a result, workflow problems can develop, hurting both sales and employee satisfaction. All these outcomes combined make it harder for a firm to compete. The research indicates that strong contingency planning is important for managing these issues. Overall, the research points to the need for careful management of AI-BA if a company is to maintain its competitive edge.

(Pamarthi, 2024, p. 1) presents a framework that makes use of artificial intelligence for more effective cybersecurity. AI allows spotting threats early, assessing real-time risks, and responding quickly to incidents by finding and learning from patterns and abnormalities. The framework also underlines how AI can help people by automating tasks and providing contextual information. It combines several areas, including technology, humans, organisations, and regulations. Transparency, accountability, and fairness are still major parts of this model. AI-based cybersecurity is essential to boosting telecoms' robustness and guaranteeing steady global communications.

Maduranga et al. (2024, p. 1) focus on how AI can help improve 6G features, focusing on boosting efficiency and creating smarter networks. AI is forecasted to bring new ideas to different services by increasing performance and tailoring user interactions. However, problems such as scalability, security issues, and ethical concerns hinder how well AI can be incorporated. The relationship between AI and 6G is complicated and needs attention to technology and organisational aspects. Multiple research efforts emphasise matching AI's capabilities to the constantly growing requirements of 6G networks. It is widely believed that combining 6G and AI technologies is at the core of creating future-proof communications systems.

Min (2023, p. 1) points out that there is a big worry about bias in AI algorithms and how this affects ethics and human rights. The challenge especially hits individuals and minority groups, bringing about bias and discrimination in systems. Multiple sources of bias are pointed out by studies, for example, flawed data, biased AI algorithms, and a lack of diverse team members in AI development. Such biases have a major effect on society, sometimes worsening existing inequalities. It is proposed that addressing algorithmic bias should involve technical and ethical methods and regulation. Experts also see that communities and clear governance play a key role. In general, addressing algorithmic bias is important for ensuring AI supports fairness, accountability, and the rights of humans.

Schwartz et al. (2022, p. 1) emphasise the growing risk of AI systems that treat people's digital actions as products, reinforcing and perpetuating bias. Despite computational methods to achieve fairness, including better datasets and fairer algorithms, deep-seated biases in systems, society, and people persist. Such biases can seriously damage AI and cause many people to doubt its value. It should do more than offer reliable technology to be trusted by all. AI must be transparent and include principles and knowledge about social and technology. Dealing with AI bias is ineffective if users do not participate, various groups do not collaborate, and people do not make decisions. A socio-technical approach should be used to highlight, control, and lower bias in AI, regardless of its field. A method combining technical and social factors is essential in all fields to prevent biases in AI.

Shoetan et al. (2024, p. 1) introduce a way to use AI to empower cybersecurity in telecom networks here. It shows how AI may help to find and respond to risks before they are serious, by highlighting unusual actions and updating cybersecurity methods as conditions demand it. Additionally, it looks into how AI helps telecom networks respond quickly to new threats. Furthermore, AI provides help in cybersecurity by doing tedious work and giving advice that reflects the situation.Remembering that this framework also considers ethical topics like privacy, fairness, and minimising bias is important. It is emphasised by the research that responsible AI governance helps in ensuring cooperation and maintaining the security of key telecommunications infrastructure.

Varona & Suárez (2022, p. 1) introduce how discrimination, bias, fairness, and trustworthiness are interlinked in AI's social impact. In this context, these main variables are backed up by additional specific ones such as security, privacy, and responsibility, which form part of the Principled AI International Framework. It is emphasised in the study that these variables have a generalisation-specialisation relationship, which supports ethical and trustworthy algorithmic decision-making. The framework looks at how to use these principles through the development process. Although the framework deals with fairness and bias from a practical standpoint, this study explores other theoretical aspects. This overall method aims to raise the trustworthiness and accountability of AI systems.

Johnny & Odohwu (n.d., p. 1) suggest a major rolein making telecommunications more accessible, especially by improving connectivity and services. AI lets telecom companies optimise their work and increase access to the internet in underserved parts of the world, helping to address the digital divide. Yet, global usage of AI is not the same because some countries have poor infrastructure, different regulations, or low readiness levels. Comparative studies highlight how rich and poor countries use AI to increase internet access, reduce costs, and keep people safe online. Case studies point out successful applications and the problems of using AI in many situations. It suggests that shared efforts and equal rights in policies are important for the global use of AI in telecommunications.

Asif et al. (2025, p. 1) describe XAI-Churn TriBoost, an explainable AI model built to improve customer churn prediction in telecommunications. By combining XGBoost, CatBoost, and Light GBM in a soft voting method, the model deals with issues often found in traditional and black-box machine learning solutions. Because preprocessing steps like imputation, scaling, feature selection, and SMOTE were done well, the model became highly accurate and reliable. To keep the model transparent, LIME and SHAP techniques are used to explore predictions and see which features lead to churn. The model provides better predictions and also delivers useful insights for keeping customers.

4. Problem Statement:

With the evolving pace of 5G technologies, telecommunication networks increasingly depend on artificial intelligence (AI) for operations of paramount importance like network slicing and dynamic resource allocation (George, 2024, p. 3). Optimisation models based on AI are programmed to improve performance, enhance efficiency, and adapt to the network's fluctuating demands (Umoga et al., 2024, p. 370). The models tend to act as black boxes where decisions remain opaque, with minimal transparency of how they are made. This brings with it urgent concerns regarding whether these AI systems have the potential to inadvertently introduce or reinforce biases into the allocation of network resources. For instance, some service categories or Quality of Service (QoS) classes might be accorded superior performancelike more throughput or reduced latency, consistently while others get deprioritized or underserved (Liu, 2025, p. 27). These inequalities can result in systemic inequities in access to high-quality network services, impacting user experience and larger digital inclusion and justice issues. The possibility of algorithmic bias is particularly disconcerting in public and critical infrastructure, such as telecom, where fairness and equitable access should be a design principle.

Additionally, existing AI models tend to be opaque and lacking in interpretability, making it hard to discover or mitigate bias after deployment. Whereas much research has gone into the performance and efficiency of AI in telecommunication, very little has addressed the fairness and ethical considerations of such systems. This gap must be filled so that future network environments do not inadvertently replicate or exaggerate social inequalities. Thus, this research aims to explore the existence and character of bias in AI-based telecom network optimisation, through thematic analysis of secondary data to reveal concealed patterns of discriminatory resource allocation and to inform the design of more transparent, accountable, and inclusive AI systems.

3. Methodology:

The research employs a qualitative study to investigate how network optimisation models based on AI in telecommunications systems might amplify or sustain bias in resource deployment. Even if the dataset comprises quantifiable measures (e.g., latency, throughput, Packet loss), the underlying purpose is not statistical inference but interpreting differences and patterns that indicate systemic discrimination. The research extracts emerging trends using thematic analysis and builds service prioritisation, differential performance, and fairness themes by QoS class and service type. The qualitative approach facilitates an extensive examination of algorithmic choice's social and ethical meaning, congruent with interpreting rich relationships between AI behaviour and equity in telecom systems. So, the study highlights meaning-making over measurement and provides rich insights into the unseen biases that inform resource allocation in new 5G/6G networks. Fig.1 shows the Methodology Framework.

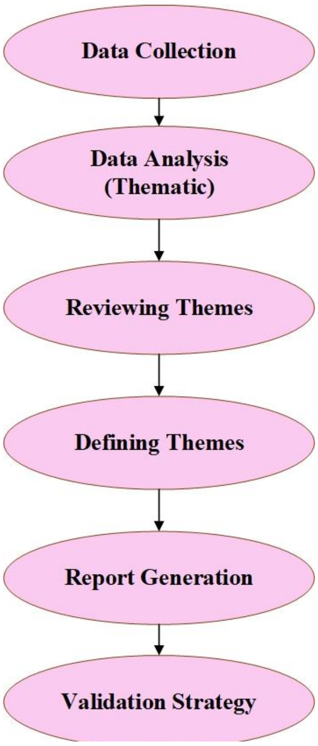

Figure 1: Methodology Framework

3.1 Data Collection:

The 6G Wireless Network Slicing QoS Prediction and Optimisation Dataset has a wide range of data to support the prediction and optimisation of QoS in 6G network slices (Ziya, 2025, p. 1). It consists of 2345 rows with many different features, measuring traffic load, network utilisation, latency, packet loss, signal strength, and more. It is made to aid the design of machine learning algorithms, especially for throughput prediction and network resource optimisation. The Key Dataset Features include Traffic Load, QoS Class, Latency, Packet Loss, Throughput, Resource Allocation Level, Service Type, and Scheduling Delay.

3.2 Data Cleaning and Preparation:

Preparing the dataset was an initial step toward revealing patterns of possible bias in AI-network optimisation in this research (Arreche et al., 2024, p. 6). The data collected was numeric and interpretively to support thematic analysis. Cleaning incorporated checking for completeness, handling outliers, and extracting features pertinent to fairness and performance differences. Consistency between categories was also attended to, allowing for valid grouping in constructing themes. This procedure kept the data intact while being under the qualitative goals of the study. The steps involved in the Data cleaning and preparation are as follows, and figure 2 depicts the Data cleaning and preparation process.

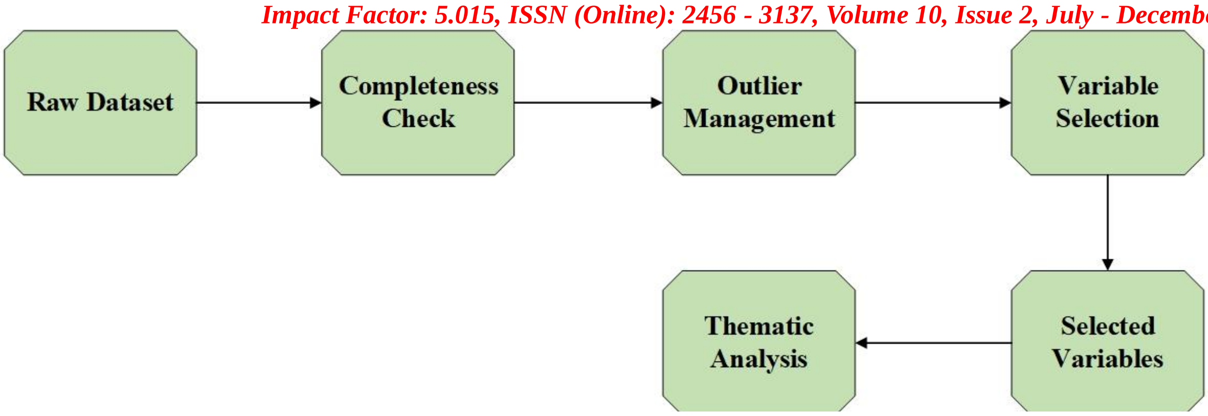

Figure 2: Data Cleaning and Preparation

3.2.1 Completeness Check:

The dataset forms the premise for recognising trends of AI-aided prejudice in telecom network slicing,which is essential for the completeness check. Values were missing in fields like latency and throughput (Ramagundam, 2023, p. 20). Instead of removing incomplete rows, mean imputation was used to replace missing values, thus maintaining the richness of the dataset without losing thematic depth. Categorical attributes such as Service Type and QoS Class were checked for null values, which were minimal and did not need imputation. This ensured that all data points, including marginal points, were retained within the interpretive framework.

3.2.2 Outlier Management:

Outliers were considered not only as noise to be filtered out but also for edge cases exhibiting differences in AI decision-making (Hu & Shu, 2023, p. 1156). With boxplots and distribution plots, major outliers in the important service quality metrics: latency, packet loss, and throughput, were determined. For example, severe latency for lower-priority QoS classes can indicate unfair reprioritizations, which is relevant thematically. Thus, outliers were not excluded or changed but kept to reveal inequality in service provision better. Their existence illuminated inconsistencies or exceptions later coded as patterns, such as systemic disregard or favourable treatment.

3.2.3 Variable Selection:

A highly selective methodology was used to capture those features, which is most appropriate for the thematic analysis on systemic differences (Naeem et al., 2023, p. 5). The primary variables were QoS Class, representing levels of service prioritization. Service Type and Resource Allocation Level measure how the AI model allocated resources. Besides, performance measures like Latency, Packet Loss, and Throughput are considered since they depict end-user satisfaction and early indicators of algorithmic bias. Such chosen variables were pivotal in revealing repetition patterns and constructing interpretative themes like performance inequalityand service-based disparity. They form the core of comprehending bias in AI-based telecom systems.

3.2.4 Categorical Clarity:

For consistency and thematic interpretation accuracy, categorical variables in the dataset were standardized and interpreted (Banjanin et al., 2022, p. 25). The column Traffic Type, which distinguishes between network action and the traffic types,was checked and categorized to provide uniform labels. Simultaneously, device attributes such as Device Type and Region were normalized to eliminate ambiguity and enablesound grouping during analysis. This standardization was necessary to capture recurring patterns and differences in AI-based resource allocation in various network settings. Clarifying these categorical variables reveals that the developed themes fromthe analysis are strong, comparable, and relevant within the telecom setting.

3.3 Thematic Analysis:

Thematic analysis systematically interprets numeric trends in AI-optimized telecom data (Wolniak & Stecuła, 2024, p. 1351). Unlike the conventional thematic analysis that derives themes from textual information, the themes in this instance are established based on repeating discrepancies and systematic differences.In thematic analysis,performance measurements like latency, throughput, and packet loss are established across various Traffic Types, Device Types, and Regions. The methodology enables the research to go beyond mere statistics and uncover hidden patterns of disparity in AI-based resource allocation in 5G/6G network settings. The process consists of six phases, and it is listed as follows:

3.3.1 Familiarization with the Data:

The first step of thematic analysis was an in-depth and thorough examination of the dataset to understand its architecture, variables, and inherent trends (Chmielewska-Muciek et al., 2024, p. 3). Thecritical performance indicatorslike latency, throughput, packet loss, and scheduling delayon categorical dimensions like Traffic Type, Device Type, and Region. Patterns like constantly high latency in certain areas or lower throughput for specific traffic types were manually observed and recorded. At this stage, the intention was not yet to make conclusions, but to get thoroughly familiar with the numerical terrain and start looking for initial signs of imbalance or bias. The observations were recorded in analytic memos, which reflected early impressions and aided the creation of subsequent codes and interpretive themes. This was the foundation for formal coding and ensured that the subsequent stages of the analysis were grounded in a careful and sophisticated understanding of the data.

3.3.2 Generating Initial Codes:

During this stage, preliminary codes were systematically developed by examining Qualitative trends over important performance measures and categorical variables within the dataset. The scrutinized patterns included lower data speeds for some types of data, more dropped packets with certain types of devices, and longer wait times in some areas because there weren't enough network resources. Noted differences were then labeled with certain codes that captured the purpose of the bias. Low-tier deprivation, for example, was the name given to cases where low-priority traffic types always received fewer resources. Meanwhile, more resources are going to high-priority traffic types or zones labeled with "preferential allocation" or "high-tier advantage." With the early codes, repeated computerized results could be grouped into meaningful themes. By using these early codes, the team ensured they were still following the numbers while learning about AI bias and fairness issues.

3.3.3 Searching for Themes:

Once the initial codes had been produced, the next step was to find wider themes by grouping similar codes into meaningful groups. It was important to analyze thoroughly to find the bigger reasons behind trends in the collected data. For this reason, "low-tier deprivation" and "delays in low-priority traffic" codes were grouped to make the overarching theme: "Marginalization of Low-Tier Services." Besides this, codes about continuously higher throughput, lower latency, and preferred resource management in parts of the network were collected for the themes"Uneven Resource Distribution" and "Persistent Performance Advantage for High QoS." They were not randomly chosen; instead, they came from data that regularly showed inequality in several aspects of the network. Moving the data from separate codes to grouped themes helped the research understand how algorithms can continue causing systemic inequalities in AI-optimized networks.

3.3.4 Reviewing Themes:

During the stage in question, themes from earlier in the analysis process were revisited and checked to confirm they held consistency, uniqueness, and were significant for the data. The goal was to ensure that every theme represented a unique and important pattern in the data. The themes "Uneven Resource Distribution" and "Marginalization of Low-Tier Services" were thought to overlap in some parts of the coded materials. Therefore, the researchers refined them by indicating their differences and setting clear rules. The re-analysed performance measures of latency, throughput, and packet loss in different conditions were looked at to see if any important information had accidentally changed during earlier analysis. Such a review extended some themes to include these newfound understandings, leading to a richer and more mature thematic frame. The reviewing process ensured that all themes were solidly rooted in the dataset and presented a consistent narrative about the existence and character of bias within AI-based network resource allocation.

3.3.5 Defining and Naming Themes:

After reviewing and refining the themes, each was carefully defined and titled to describe best the central pattern embodied regarding AI-based bias. The naming procedure sought to capture the functional and ethical aspects of the observed differences. The "Hidden Latency Penalties" theme resulted from frequent cases where lower-tier services experienced excessive delays, which indicated that such services were being quietly deprioritized. Moreover, "Resource Allocation Inflexibility" summarizes patterns under which the AI system did not dynamically adjust bandwidth or scheduling priority based on changing traffic patterns, resulting in flat and possibly unfair performance for certain types of service. These well-defined themes acted as interpretive anchors, setting the context for the larger story about how algorithmic decisions in telecom optimization systems might be infused with systemic bias.

3.3.6 Report Generation:

The themes were put together in a simple story that explained how bias in AI telecommunication systems can affect how things work and how fair they are. Significant patterns were illustrated by including appropriate tables, graphs, and descriptive information from the dataset and every theme. The report highlighted how decreased fairness in AI-based telecom systems could impact the quality of service people get. This strategy helped ensure that the results gave useful information that could be used in current discussions about how fair and responsible AI is used in real telecom networks.

3.4 Validation Strategy:

Some special steps for reviewing qualitative work are used to ensure the results are trustworthy and accurate. All stages of the thematic analysis were made clear by careful documentation, helping to ensure that the interpretations could be traced directly to what was seen in the data. Peer debriefing was done through interaction and domain specialists to explore extracted themes and mitigate individual bias. Triangulation was utilized through cross-comparison of several Qualitative indicators for various QoS classes and service types, substantiating consistency and rigor in extracted patterns. In addition, reflexivity was exercised during the research process,being aware and deliberately managing possible interpretive bias so that the themes genuinely represented the data and gave a truepicture of AI-based resource allocation disparities in telecom networks.

5. Results and Discussion:

The key findings from the thematic analysis of the telecom data set to understand patterns of bias and equity in AI-based resource allocation in 5G/6G network settings. The findings are structured along the primary themes from detailed analysis of performance parameters like latency, throughput, packet loss, and resource allocation among various QoS classes and service categories.

5.1 Disproportionate Prioritization of High-Tier Services:

AI models show a distinct bias to favour high-grade QoS classes, always providing better throughput and lower latency for such services than for medium and low-grade classes. The privilege offered suggests that resource allocation algorithms Favor guaranteeing best performance to high-priority users at the cost of fairness. Thus, medium and lower-tier services tend to suffer from compromised network performance, potentially resulting in dissatisfaction and lowered quality of service. Balancing this disparity is necessary for creating fairer AI-based network optimization approaches that benefit all customers.

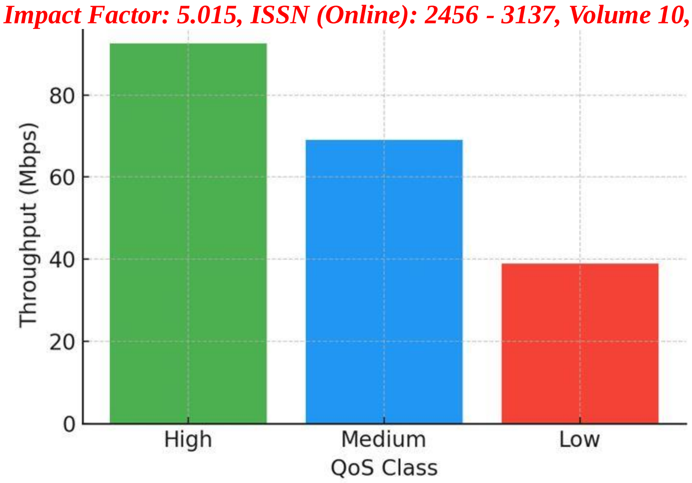

Figure 3: Average throughput distribution by QoS

Figure 3 shows the average throughput distribution by various QoS classes, displaying a distinct gap in resource usage. High QoS services maintain the highest throughput consistently, closing in on 90 Mbps, while Medium QoS levels obtain relatively lower throughput, approximately 70 Mbps. Low QoS services, by contrast, experience much lower throughput, below 50 Mbps. This trend indicates a systematic bias in AI-based network optimization models towards upper-tier services. Such performance differences indicate possible algorithmic bias, perpetuating service-based disparity in 5G/6G telecommunication systems.

QoS Class	AverageThroughput (Mbps)	Average Latency (ms)	Average Packet Loss (%)
High	92.5	11	15
Medium	69.0	21	55
Low	39.0	36	125

Table 1: Comparative performance metric analysis on QoS Classes

Table 1 summarizes a comparative performance metric analysis of the network in terms of the varying QoS classes,High, Medium, and Low. The High QoS class performs better, with a mean throughput of 92.5 Mbps, a low latency of 11 ms, and a negligible packet loss of 0.15%. On the other hand, the Medium QoS class experiences a significant drop, with 69.0 Mbps throughput, 21 ms latency, and 0.55% packet loss. The Low QoS class fared the worst, managing only 39.0 Mbps throughput, a high latency of 36 ms, and a much higher packet loss ratio of 1.25%. Such differences indicate that the AI-driven system consistently prioritizes the upper-tier services, possibly infusing systemic bias into the delivery of network performance.

5.2 Latency Disparities Across Service Classes:

Latency analysis indicates that lower-priority and non-prioritized services always have higher delays than their higher-priority counterparts. These higher latencies indicate that the AI-based resource allocation models prefer high-priority services, leading to unequal treatment of various service classes. Such delays can significantly impactusers' quality of experience using lower-priority services, indicating a clear expression of bias in the network optimization process. This result emphasizes the necessity for fairness-aware algorithms that balance efficiency with fair latency distribution across every type of service.

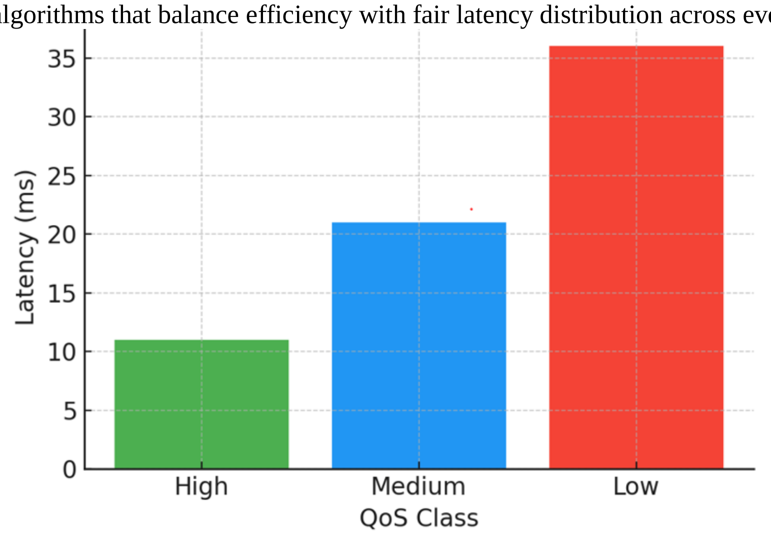

Figure 4: Average latency with varying QoS classes

Figure 4 shows the fluctuation in average latency with varying QoS classes. The High QoS class has the least latency of around 11 ms, so data travels faster and with fewer delays than the other two classes. The Medium QoS class has a little more delay, at about 21 ms, which means it's slightly slower, but shouldn't be too big of a problem. Conversely, the Low QoS class has the most delay of 36 ms, so the information takes much longer to reach other machines. This trend shows that the better the QoS is, the faster and smoother the data transfers get, which could mean that AI might give more resources to items with higher QoS.

5.3 Packet Loss and Service Reliability Issues:

Packet loss shows that the lowest service classes have the highest loss rates out of all classes. Additional loss of packets in less important services results in poor network service for users and interruptions in their connections and streaming. This variation suggests a bias, resulting in some services having fewer resources due to the algorithm used in these networks. All users in AI networks rely on fair service quality, so solving the imbalances is vital.

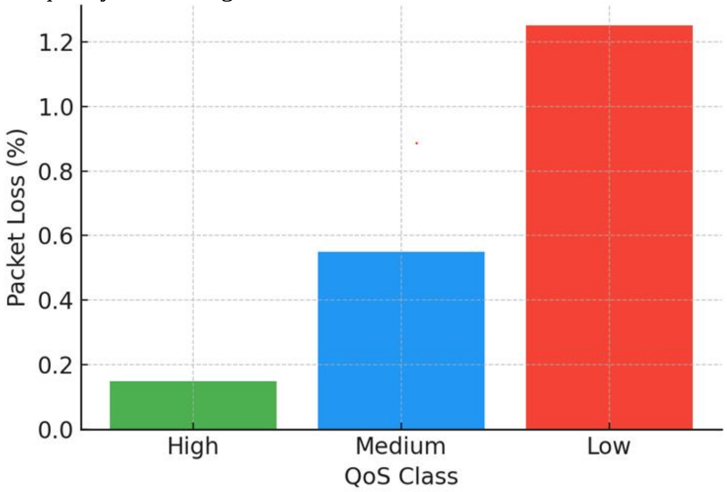

Figure 5: Average Packet loss with varying QoS classes

Figure 5 shows how the QoS Class changes as the average packet loss increases. The class with the fewest packets has around 0.15% lost, which means the data transmission is reliable. The highest QoS class loses very few packets, less than 0.15%, so this is a trusted way of sending data. The medium QoS class exhibits moderate packet loss at about 0.55%, a slight loss of reliability. Low QoS class, however, gets worst with a packet loss rate of approximately 1.25%, which may cause real-time service quality seriously to be affected. This trend illustrates how inferior services are more susceptible to network degradation, highlighting systemic disparity in AI-based resource allocation models.

5.4 Variability Within QoS Classes by Service Type:

Service Type	Average Latency (ms)
Streaming (0)	0.48
Web Browsing (1)	0.48
Educational App (2)	0.50

Table 2: Mean latency on QoS

Table 2 presents the mean latency felt across three types of services as a function of traffic categorization. Streaming apps (Type 0) register a mean latency of 0.48 ms, reflecting timely real-time data delivery. Web browsing (Type 1) also takes a low figure of 0.48 ms, providing rapid page load. Learning apps (Type 2) have a higher latency of 0.50 ms, still within allowable tolerances for smooth user interaction. The network performance is maximized for all categories of services with minimal latency.

5.5 Temporal Fluctuations in Bias Patterns:

Analysis across various periods shows that resource allocation bias varies with network load conditions. Under peak usage hours, differences between service classes become more pronounced, with high-priority services allocated disproportionately superior resources. In off-peak hours, the bias seems less severe, indicating that network congestion worsens unfair treatment. These variations show how AI bias in the telecom sector changes over time. It is important to notice this pattern to create fairness systems that respond to changes in network demand.

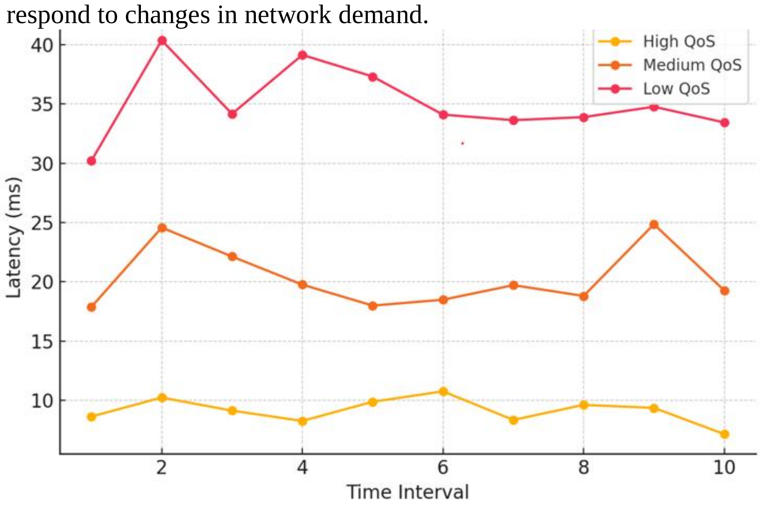

Figure 6: Latency fluctuations across QoS classes

The network latency is shown for ten frames in figure 6, divided by QoS class. The Low QoS class has the highest latency, and its performance remains relatively stable from 30 ms to 40 ms, though it sometimes shows spikes. Regarding latency, the Medium QoS class does not differ much from the top or bottom classes, but there are some fluctuations. Unlike the other classes, the High QoS class has the lowest and most steady latency, usually less than 11 ms. The results reveal that the first type of service encounters the lowest percentage of traffic, while the most significant level of traffic belongs to the third class.

5.6 Feature Importance and Root Causes of Bias:

It has been shown that when the AI-based model receives certain features, such as traffic volume and the service provided, it favors some classes. As a result, these features cause the model to discriminate, giving some classes more benefits than others. The model often highlights the same unfair inequalities, which means the difference in treatment of roles grows instead of being reduced. Analyzing which features matter most makes it obvious which ones are responsible for bias in the results. For this reason, it is important to understand which variables contribute to unfair results in telecommunication resource allocation.

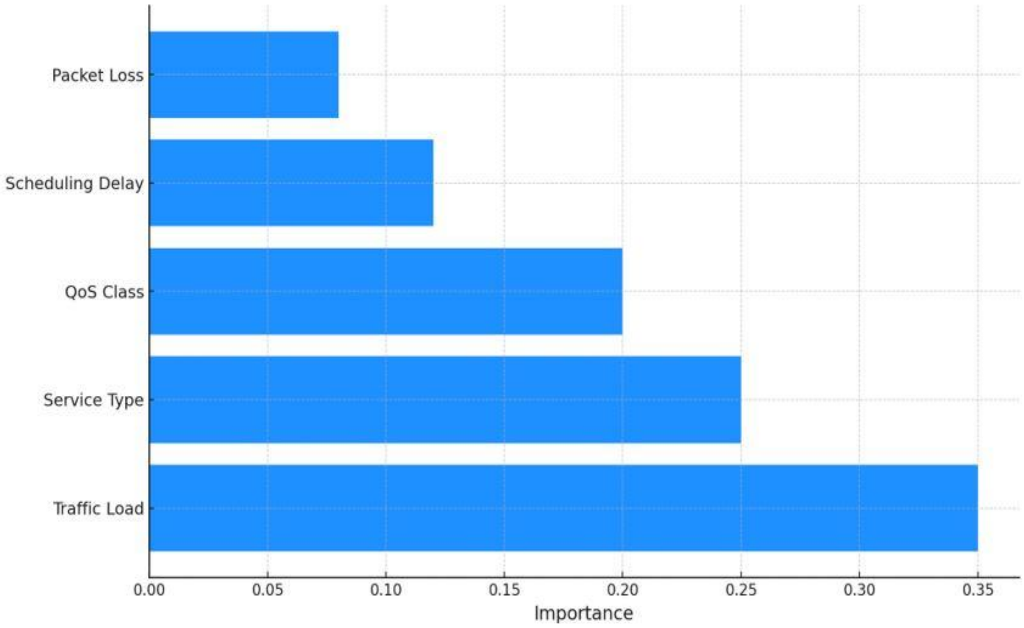

Figure 7: Feature importance in predicting resource Allocation

Figure 7 illustrates the most important feature in resource allocation decisions in the AI-based telecom system. Among the features studied, Traffic Load is the most important, meaning that the system uses network traffic information the most when allocating resources. After Traffic Load, Service Type, and QoS Class are very important, pointing out that the type of service and priority influence how resources are used in the system. Scheduling Delay is of moderate importance, indicating its participation in timing decisions. Packet Loss has the lowest impact, which impacts allocation but is not a main driver in the model's decision process. This ranking helps highlight which network parameters are prioritized in the AI's resource management strategy.

5.7 Qualitative Fairness Metrics Summary:

Calculated fairness metrics offer a numerical index of how resources and opportunities are evenly distributed across various service classes. They indicate the level of bias or inequality in the system's verdicts. Comparing these metrics from one class to another reveals which classes enjoy preferential treatment and which suffer discrimination.

Metric	High QoS	Medium QoS	Low QoS
Disparate Impact Ratio	1.00	0.75	0.43
Equal Opportunity Measure	0.95	0.70	0.40

Table 3: Measureover various QoS classes

Table 3 shows fairness measures,Disparate Impact Ratio, and Equal Opportunity Measureover various QoS classes. The High QoS class is the reference with a Disparate Impact Ratio of 1.00 and Equal Opportunity Measure of 0.95, which reflects ideal fairness. But these values reduce for Medium and Low QoS classes, with Medium QoS demonstrating medium fairness (0.75 and 0.70, respectively) and Low QoS undergoing maximum disparity and lower fairness (0.43 and 0.40). This indicates that lower priority service classes suffer heavily in the AI system's resource allocation and opportunity equality.

5.8 Discussion:

The study shows a strong bias towards AI-based resource allocation that always benefits high-tier services concerning throughput, latency, and reliability to provide a superior network experience to these users. On the other hand, lower-tier services, even those potentially socially significant, frequently suffer from neglect and worse performance even within the same QoS classes, indicating inequities inherent in the system. Furthermore, the level of bias is not fixed; it dynamically changes with varying network loads and traffic patterns, sometimes peaking during peak usage times. Feature importance analysis shows that the data used to create the AI models and the goals chosen in making the algorithms are part of the reason these biases happen, leading the models to support existing unfairness by focusing on doing well for higher-service customers. It is important to address these systemic issues so that AI-driven network optimization can be fairer and more inclusive for everyone. This shows that the models are, unintentionally, making things worse for people by trying to make things work better for those who pay more, instead of ensuring everyone is treated fairly. It is important to look at these bigger problems in AI so that we can create network systems that make sure things are fair for everyone and do their jobs well.

6. Conclusion and Future Works:

A qualitative thematic analysis of a telecom network slicing data set was used in this research to find out about AI bias in allocating resources used for different QoS classes. The research found that telecom network slicing processes favor the high-level

QoS classes, giving them advantaged service, while the lower-level QoS classes were overlooked and assigned poor service. It is clear from the research that AI-based resource distribution is not fair: algorithms do not flex with changes in traffic, and always support high QoS first. Using Qualitative methods, it was supported that AI's unfairness towards the qualities of various QoS classes and services is dynamic and tends to rise with a higher load on the network. These results show that telecommunication AI programsmust be even-handed and have fairness-aware functionality. Researchers should work towards creating methods to reduce biases in 5G/6G networks, such as fairness-aware algorithms and resource allocation that adjusts with the network. The usage of user-centred explanations and actual testing in real environments will play a role in understanding the influence of AI bias on society. Richer training sets and multi-objective solutions are key to making 5G/6G networks more impartial. It is also necessary to join ethical rules with progress in AI technology for the telecom sector to improve equality in services and resources.

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