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A Triangulation-Based Approach for 4G LTE Networks Performance Evaluation Using Machine Learning

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ABSTRACT

In today's digital world, the widespread use of smart devices and high-bandwidth applications places significant pressure on 4G LTE networks, leading to performance issues such as increased latency, reduced throughput, network congestion, and service degradation. To address these challenges, this study introduces a triangulation approach for evaluating and optimizing 4G LTE network performance using machine learning. Triangulation, in this context, means integrating both multiple data measurements (data-level integration) and multiple analytical algorithms (model-level integration) to enhance result reliability, validity, and generalizability. Using a real-world dataset from a Nigerian network provider containing 910 data points across 257 features, a composite performance metric TCMD (Throughput, Channel Quality Indicator, Max Users, and Download PRB Utilization) was engineered to represent network performance. Fourteen machine learning models were evaluated, with Support Vector Regressor (SVR) and Gradient Boost Regressor (GBR) identified as top performers. A hybrid model combining both SVR and GBR was then developed and applied. The results demonstrated notable improvements, with the hybrid model achieving strong predictive performance with $R^2 = 0.74$, $MSE = 0.187$, and $MAE = 0.332$. The model successfully resolved approximately 70% of moderate performance issues (bottlenecks) and improved the overall network quality. In conclusion, the hybrid ML-triangulation framework provides a reliable foundation for future LTE/5G performance optimization and predictive network management.

17. INTRODUCTION

Over the past decade, advancements in cellular network technologies have brought about significant transformations, profoundly affecting both professional and personal activities. The evolution in mobile network, particularly with the rollout and expansion of 4G LTE (Long-Term Evolution) networks, has enabled the widespread adoption of smart devices. These devices, which include smartphones, tablets, wearables, and other connected technologies, serve as essential tools in facilitating a broad range of data-intensive applications, including real-time communication, online gaming, high-definition video streaming, virtual reality (VR) experiences, and cloud-based services. As users continue to rely on these technologies for both work and leisure, the demand for fast, reliable, and seamless connectivity has continued to increase dramatically (Al-Thaedan *et al.*, 2024; Elsherbiny *et al.*, 2020). This growing demand for these services, has placed immense strain on existing 4G LTE networks, which were not originally designed to handle such a high volume of data traffic. Consequently, network traffic has been increasing at an exponential rate, with millions of users simultaneously transmitting large amounts of data. This rapid increase in data traffic has in turn, introduced two key challenges for network operators and users alike namely: poor network performance and degradation in Quality of Service (QoS) respectively (Mohammed *et al.*, 2021). The evaluation of 4G LTE network performance has become critical in ensuring that cellular networks can handle the increasing demand from users, while maintaining the high-performance standards required by modern applications. Network assessment methods such as network data analysis, network simulations, and Machine Learning (ML) Algorithms have been widely used to evaluate network quality. However, each method, when used in isolation, presents inherent limitations in scope, scale, or accuracy. To overcome these shortcomings, this paper adopts a triangulation-based approach to 4G LTE network performance analysis; by integrating multiple network measurements, with several machine learning models. This method enhances the reliability, validity, and generalizability of performance evaluations. Triangulation enables cross-validation of results and better captures real-world user experiences (Ali-Yahiya, 2011; Al-Thaedan *et al.*, 2024; Karani *et al.*, 2022; Mohammed *et al.*, 2021). This study examines the integration of machine learning with the triangulation approach, to analyse and predict network performance using Key Performance Indicators (KPIs) in 4G LTE networks. The study implemented and evaluated various ML models capable of predicting network performance. The various models' performance was evaluated based on multiple evaluation metrics, followed by an in-depth comparative analysis. To the best of our knowledge, this is the first study to apply the triangulation approach in analysing 4G LTE network performance.

A. Literature Review

Modern mobile communication systems continue to rely on 4G LTE networks as their foundational infrastructure. These networks act as the primary point of entry to emerging technologies, such as 5G, which are often deployed as non-standalone (NSA) configurations. In NSA deployments, users must first be registered on the 4G LTE network before they can access 5G services. This dependency will persist until 5G standalone (SA) networks become more widely deployed and 5G-capable user equipment's (UEs) becomes more readily available (Biernacki, 2024; Minovski *et al*., 2021). Consequently, despite being an earlier-generation technology, 4G LTE network remains critical for ensuring seamless user experiences and offer valuable insights that can inform the development and optimisation of next-generation networks.

Numerous research studies have explored the relationship between Quality of Service (QoS), network performance and user perception. Some of such studies are theose of Minovski *et al* (2021) and Charonyktakis *et al* (2016) where they examined the impact of network performance on QoS. In their work, they asserted that QoS is not merely a technical measure of network performance but also a critical factor that influences user satisfaction and experience. They emphasized that factors such as throughput, latency, bandwidth, and packet loss significantly shape users' perceptions of service quality, particularly for data-intensive or real-time applications. Moreover, their findings suggest that a decline in QoS often leads to increased user dissatisfaction (Charonyktakis *et al.*, 2016; Minovski *et al.*, 2021). Thus, to evaluate the performance of a network, operators rely on various Performance metrics (PMs) such as throughput, latency, packet loss, signal quality (RSRP), network availability, etc *(*Akram *et al.*, 2023; Karani *et al.*, 2022). These PMs helps to identify areas for optimization and are used to calculate standardized Key Performance Indicators (KPIs) which are grouped by 3GPP into several categories namely: accessibility, retainability, mobility, integrity, and availability (Krasniqi *et al.*, 2018). Typically, KPIs are derived from data collected by monitoring tools embedded in network elements or through drive test. Traditionally, analysis methods for the obtained data are often manual or rule-based. However, the increasing volume and complexity of network data make such approaches inefficient and time-consuming. As a result, there is a growing need for a more automated and intelligent method of data analysis.

In response to these challenges, machine learning techniques that incorporates a triangulation approach have been proposed as an effective solution for enhancing network performance. This approach involves collecting and analysing large, complex datasets from multiple data points or perspectives. Thus, by doing so, it improves network management and enhances Quality of Service.

B. Machine Learning in Network Performance Analysis

Machine learning (ML) has seen rapid adoption in the telecommunications sector, particularly for tasks such as predictive maintenance, anomaly detection, and network optimization. While these methods show promising results in performance prediction and network optimization, their accuracy can be further improved through the integration of triangulation techniques. ML techniques, such as supervised learning, unsupervised learning, and reinforcement learning, have been successfully applied to various tasks within network performance analysis, including fault detection, traffic forecasting, and performance optimization.

Several studies have demonstrated the potential of ML in network performance analysis. For instance Riihijarvi & Mahonen, (2018), explored Machine learning (ML) techniques for network performance, by applying classical machine learning algorithms to predict network performance in scenarios where direct measurements were unavailable. Their work introduced a structured framework for categorizing prediction tasks and demonstrated the feasibility of integrating ML into network management. Similarly, Elsherbiny *et al*., (2020) expanded on this by comparing Classical ML models and time series techniques for throughput prediction using real-world LTE data. Their findings showed that classical ML, particularly Random Forest, outperformed time series models like ARIMA and LSTM. In contrast, Pramono *et al.*, (2020) focused on physical network optimization techniques such as antenna tuning and carrier aggregation to improve KPIs like throughput and signal quality in an urban LTE-Advanced network. While their results showed significant improvements, the study did not incorporate data-driven predictive methods.

These works show the growing relevance of machine learning in mobile network performance. Building on these diverse approaches, this study adopts a triangulation-based framework that integrates various network measurement data and machine learning techniques to enable a more robust analysis of 4G LTE network performance.

C. Triangulation Techniques in Network Performance Analysis

Triangulation techniques, traditionally used in geographic positioning systems (GPS) and sensor networks, typically involve the use of multiple spatial reference points or sensor inputs to determine precise physical locations or validate environmental readings. In contrast, the triangulation approach applied in this study diverges from spatial or physical domain applications by focusing on the integration of diverse performance indicators and predictive models rather than spatial coordinates or sensor data. Specifically, this form of triangulation is designed to improve the analytical robustness of 4G LTE network performance evaluation by cross-validating results through two complementary levels: data-level integration (via a composite metric combining throughput, channel quality index, maximum users, and downlink physical resource block utilization) and model-level integration (via ensemble machine learning). This methodological triangulation is particularly suited for dynamic and non-deterministic network environments, where performance metrics can vary widely due to temporal, geographical, or user behaviour factors—challenges not typically encountered in the more deterministic frameworks of GPS or sensor triangulation.

2.0 MATERIALS AND METHODS

For a successful implementation of machine learning projects specific minimal hardware and software configurations are required. These hardware components are specially designed to support activities related to artificial intelligence (AI) and machine learning (ML). Balancing hardware components like the Graphics Processing Unit (GPU) and Central Processing Unit (CPU) is crucial to ensure high performance during model training and data preparation.

2.1 Materials and Equipment

A. Hardware Requirements

This study utilizes a MacBook Pro 2019 series with the following configurations:

1. Processor (CPU): 2.4 GHz Quad-Core Intel Core i5
2. Graphics Card (GPU): Intel Iris Plus Graphics 655 1536 MB
3. Memory (RAM): 16 GB 2133 MHz LPDDR3
4. Storage (Hard Drive): 250 GB SSD
5. Operating System (OS): MacOS Sonoma 14.5

B. Software Requirements

The various software's used during this research are:

1. Microsoft excel,
2. Microsoft Word,
3. Jupyter Notebook,
4. Visual Studio Code and
5. Python-specific.

The Microsoft excel software help to store the initial dataset obtained from the Network provides. Jupyter Notebook was used for data exploration, experimentation, and documentation, while Visual Studio Code facilitated the development process through Python-specific extensions and libraries such as Pandas, Scikit-learn, and TensorFlow.

2.5 Experimental Procedure

Triangulation is the process of combining or cross-verifying data from different sources or approaches to ensure accuracy and depth in research findings. This study adopted a triangulation-based approach that integrates multiple network performance indicators with machine learning models to enhance the reliability, validity, and generalizability of 4G LTE network performance evaluation. Triangulation was applied on two complementary levels: data-level integration, through the creation of a composite performance metric, and model-level integration, via the development of a hybrid predictive model.

A. Data Collection and Preprocessing

The dataset used in this study was obtained from a selected mobile network service provider in Nigeria. Initially comprising 910 data points across 257 features, the dataset underwent rigorous preprocessing, including outlier removal and imputation of missing values. After cleaning, 845 data points across 15 relevant features were retained for analysis. The selected features include: Co-Sector, Co-Sector PRB, Co-Sector Max Users, Co-Sector Thpt, Availability, DL PRB Utilization, Traffic (GB), User Thpt (Kbps), RRC Setup Success Rate (%), ERAB Setup Success Rate, Max User, RSSI, Channel Quality Index (CQI), %RI-1, and %RI-2.

B. Feature Selection and Composite Metric Engineering

Following data cleaning, a statistical analysis was conducted to identify patterns, trends, and performance anomalies in the network. To support the triangulation framework, feature selection was performed using a correlation matrix and heatmap to determine the most impactful metrics. Based on this analysis, four key features were identified for composite metric engineering:

i. T: Throughput,
ii. C: Channel Quality Indicator,
iii. M: Maximum Users, and
iv. D: Downlink PRB Utilisation.

A new composite metric, TCMD, was formulated to encapsulate the combined effect of these variables on network performance. The metric was defined as:

$$TCMD = \frac{(T \times w_1 + C \times w_2 + M \times w_3 + D \times w_4)}{(w_1 + w_2 + w_3 + w_4)} \quad (1)$$

Where w_1 to w_4 are the weights assigned to each feature based on their correlation strength with overall network performance.

The assigned weights were:

i. w_1 = 1.0 (Throughput),
ii. w_2 = 0.3 (CQI),
iii. w_3 = - 0.6 (Max Users), and
iv. w_4 = - 0.7 (Downlink PRB Utilization).

Substituting and simplifying yields:

$$TCMD = 0.38T + 0.12C - 0.23M - 0.27D \quad (2)$$

The negative coefficients for Max Users (M) and DL PRB Utilization (D) reflect their detrimental impact on network performance, indicating that increased user load and excessive resource usage degrade service quality.

C. Model Development and Evaluation

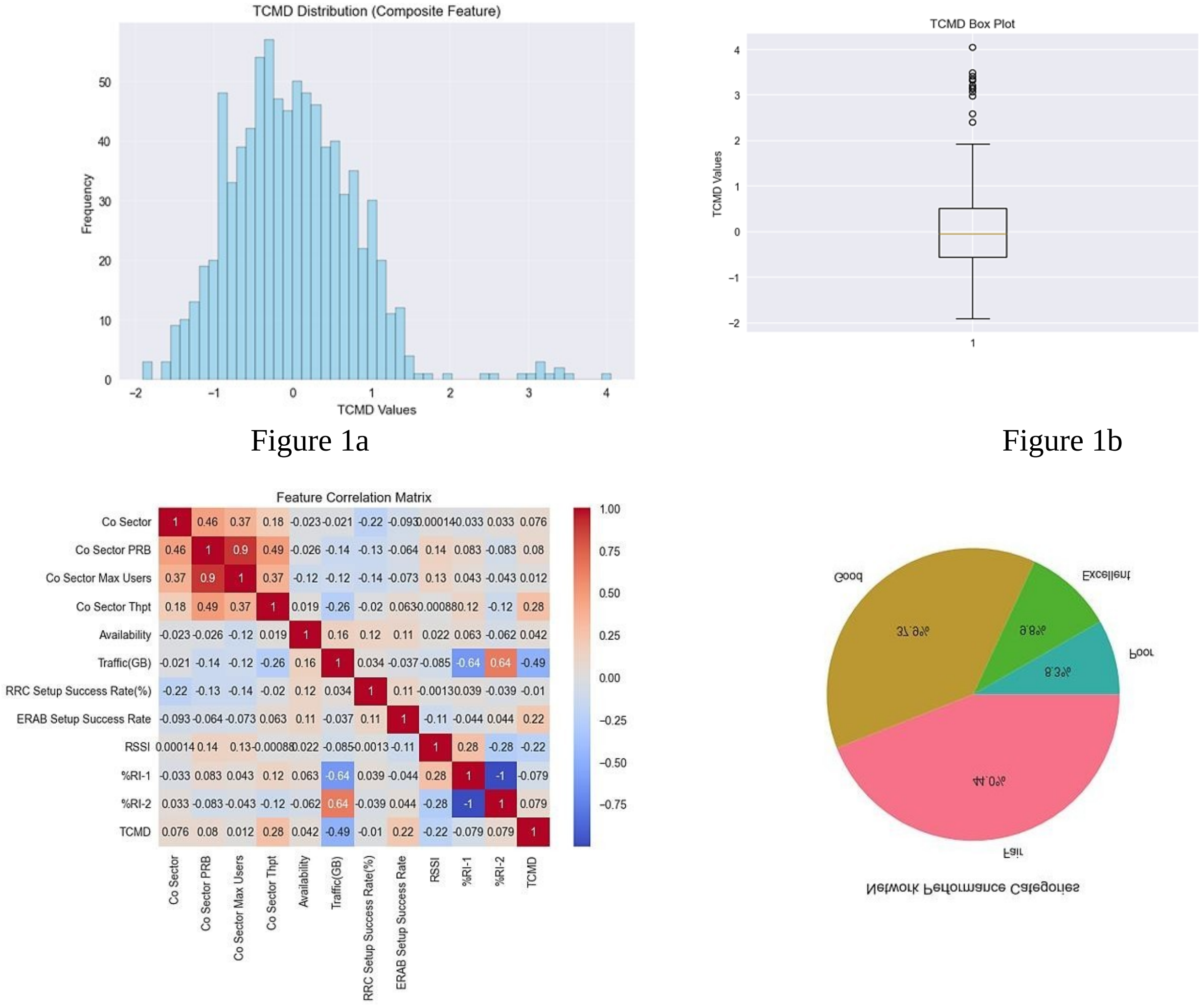
To evaluate the predictive capability of the TCMD metric, a total of fourteen machine learning models, compassing both linear and non-linear algorithms, were trained and tested. Performance was assessed using standard evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 score.

From this comparison, Support Vector Regressor (SVR) and Gradient Boosted Regressor (GBR) emerged as the top-performing models. A hybrid ensemble model was then developed by integrating SVR and GBR to leverage their complementary strengths. This hybrid model was trained using the TCMD metric alongside the cleaned dataset to improve predictive reliability and generalization.

D. Visualization and Performance Interpretation

The performance and impact of the hybrid model were evaluated through visual analysis of the network state before and after model application. Statistical visualization tools including pie charts, bar charts, histograms, and scatter plots were used to highlight key insights, identify performance bottlenecks, and demonstrate improvements. The results of this evaluation are presented in Figures 1 to 6.

18. Results and Discussion



	Co Sector	Co Sector PRB	Co Sector Max Users	Co Sector Thpt	Availability	Traffic(GB)	RRC Setup Success Rate(%)	ERAB Setup Success Rate	RSSI	%RI-1	%RI-2	TCMD
Co Sector	1	0.46	0.37	0.18	-0.023	-0.021	-0.22	-0.093	0.00014	-0.033	0.033	0.076
Co Sector PRB	0.46	1	0.9	0.49	-0.026	-0.14	-0.13	-0.064	0.14	0.083	-0.083	0.08
Co Sector Max Users	0.37	0.9	1	0.37	-0.12	-0.12	-0.14	-0.073	0.13	0.043	-0.043	0.012
Co Sector Thpt	0.18	0.49	0.37	1	0.019	-0.26	-0.02	0.063	-0.00088	0.12	-0.12	0.28
Availability	-0.023	-0.026	-0.12	0.019	1	0.16	0.12	0.11	0.022	0.063	-0.062	0.042
Traffic(GB)	-0.021	-0.14	-0.12	-0.26	0.16	1	0.034	-0.037	-0.085	-0.64	0.64	-0.49
RRC Setup Success Rate(%)	-0.22	-0.13	-0.14	-0.02	0.12	0.034	1	0.11	-0.0013	0.039	-0.039	-0.01
ERAB Setup Success Rate	-0.093	-0.064	-0.073	0.063	0.11	-0.037	0.11	1	-0.11	-0.044	0.044	0.22
RSSI	0.00014	0.14	0.13	-0.00088	0.022	-0.085	-0.0013	-0.11	1	0.28	-0.28	-0.22
%RI-1	-0.033	0.083	0.043	0.12	0.063	-0.64	0.039	-0.044	0.28	1	-1	-0.079
%RI-2	0.033	-0.083	-0.043	-0.12	-0.062	0.64	-0.039	0.044	-0.28	-1	1	0.079
TCMD	0.076	0.08	0.012	0.28	0.042	-0.49	-0.01	0.22	-0.22	-0.079	0.079	1

Figure 1a

Figure 1b

Figure 1c

Figure 1d

***Figure 1**: Network Performance Analysis Before Model Implementation*

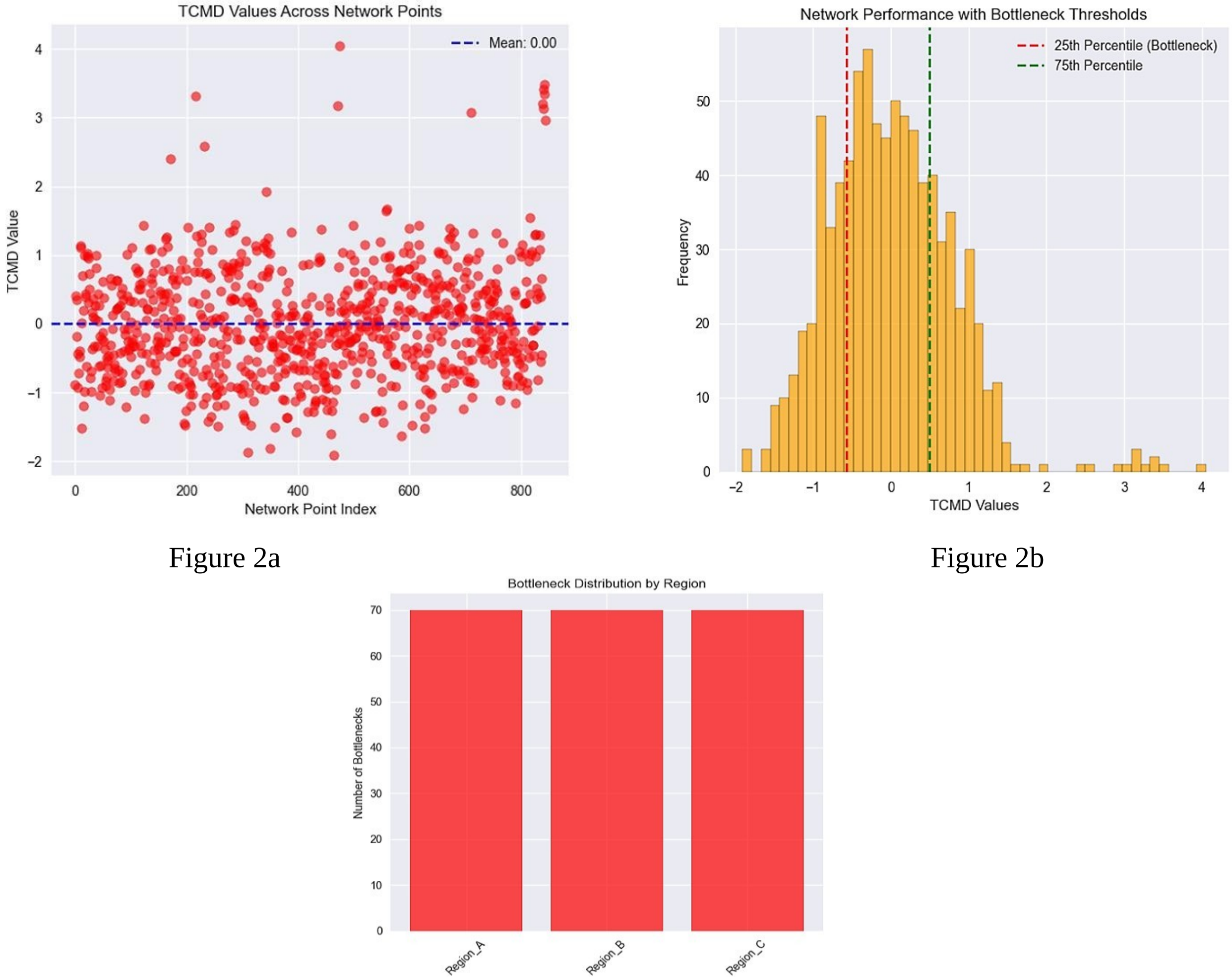


Figure 2a

Figure 2b

Figure 2c

***Figure 2**: Network Performance Analysis showing the bottlenecks*

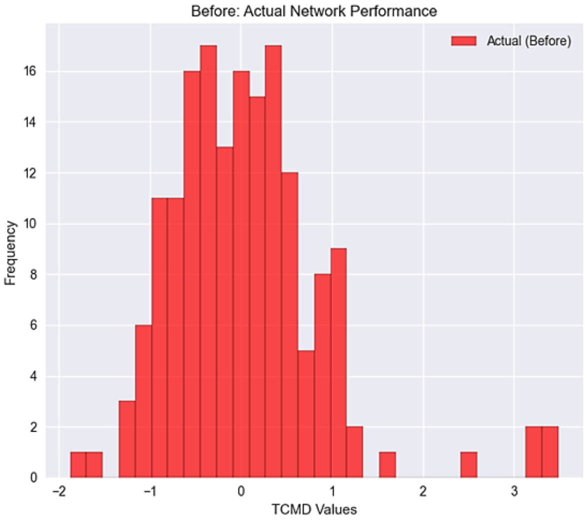


Figure 3a

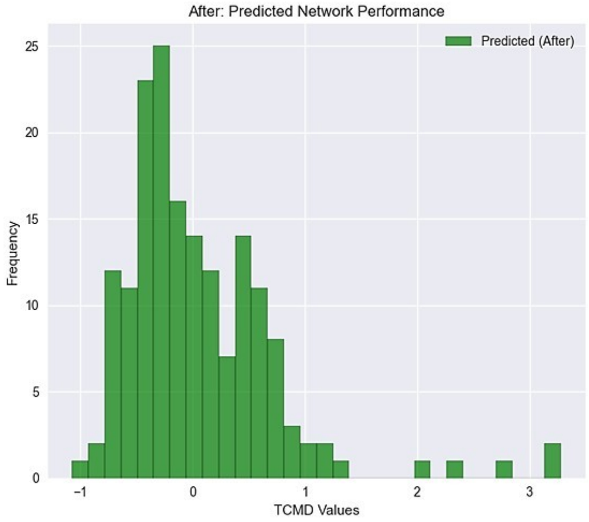


Figure 3b

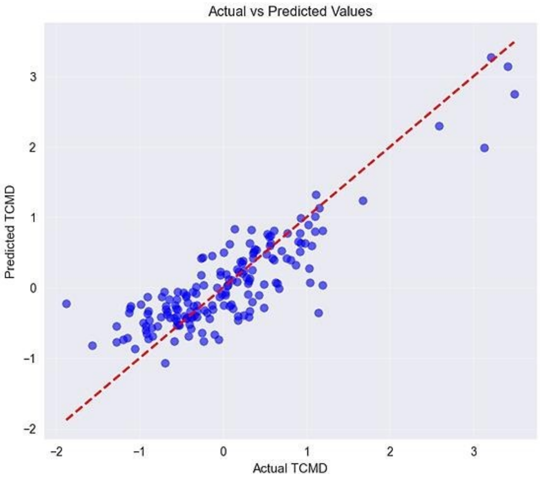


Figure 3c

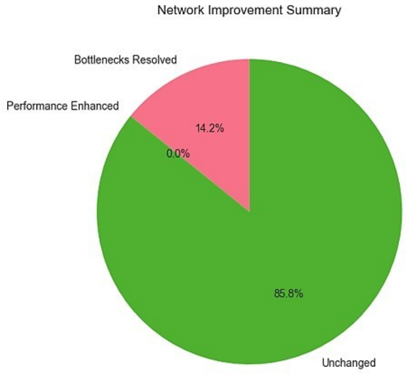


Figure 3d

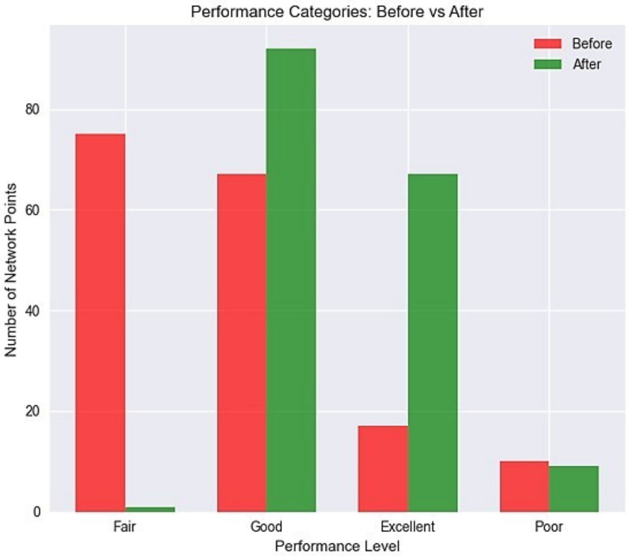


Figure 3e

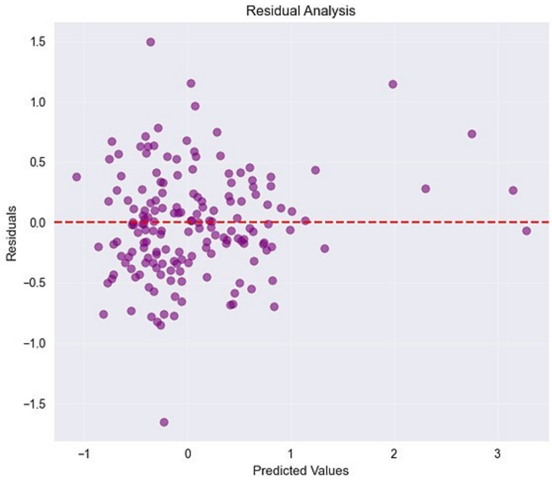


Figure 3f

***Figure 3**: Network state Before and after predictive model usage*

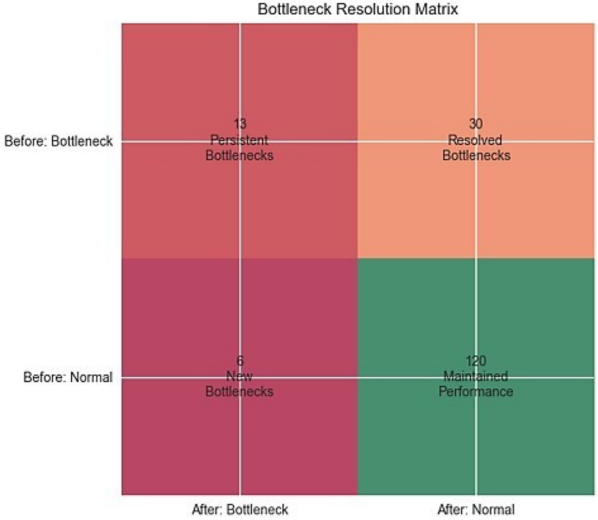


Figure 4a

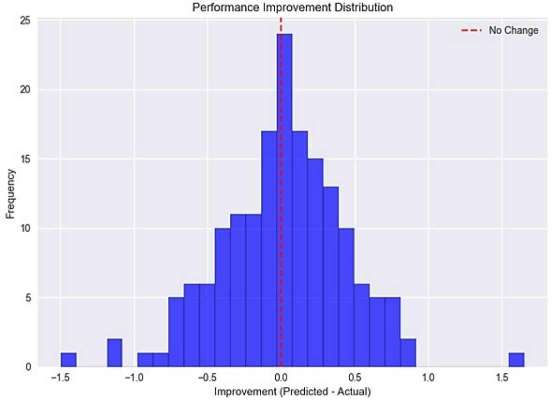


Figure 4b

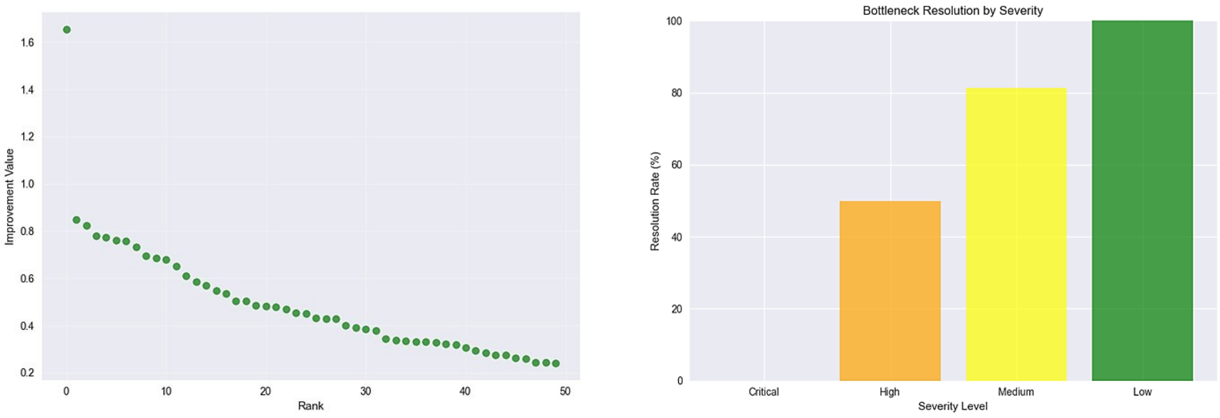


Figure 4c

Figure 4d

***Figure 4**: Bottleneck/Fault Resolution Analysis*

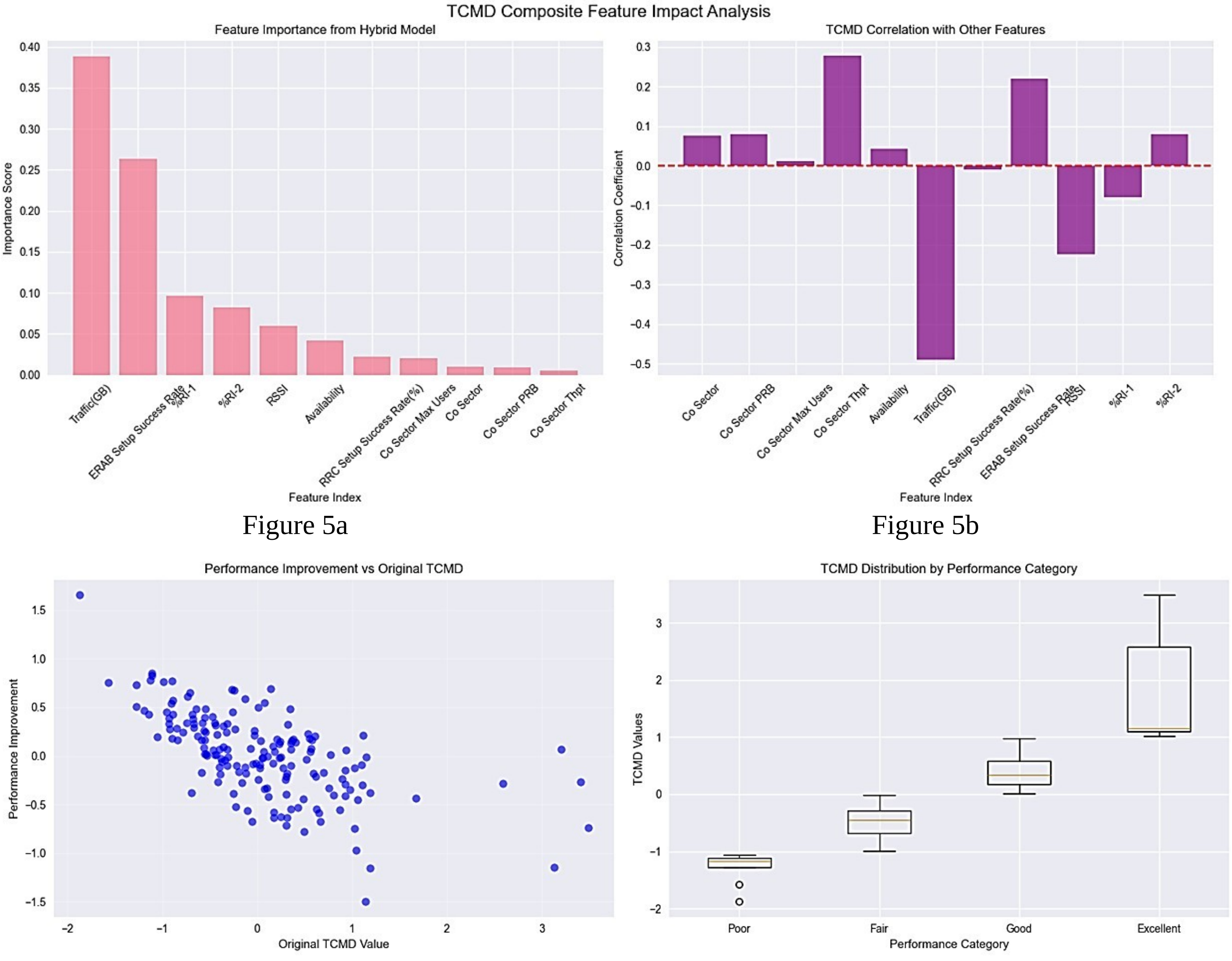


Figure 5a

Figure 5b

Figure 5c

Figure 5d

***Figure 5**: TCMD Features Impact Analysis*

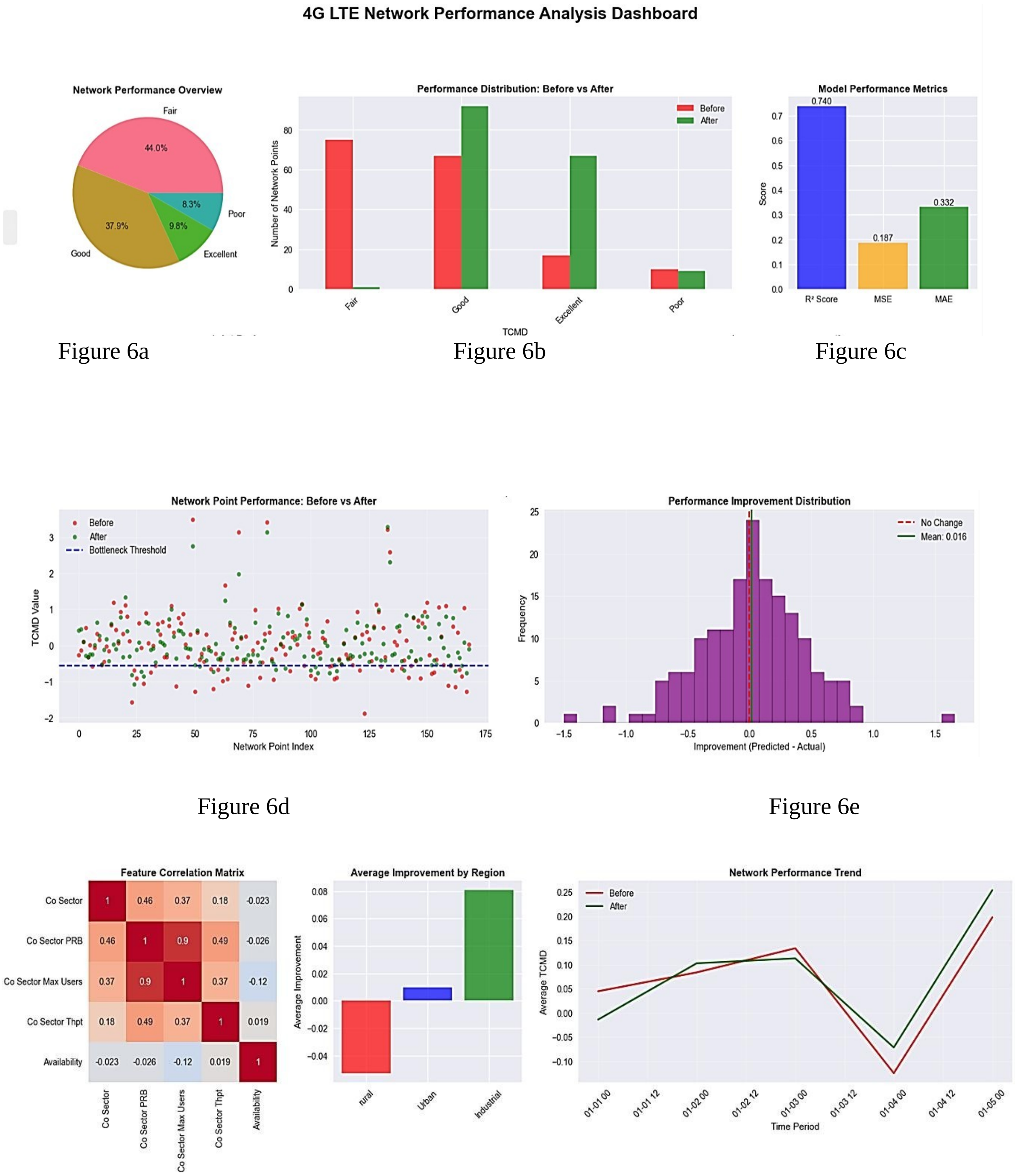


Figure 6a Figure 6b Figure 6c

Figure 6d Figure 6e

Figure 6f Figure 6g Figure 6h

	Co Sector	Co Sector PRB	Co Sector Max Users	Co Sector Thpt	Availability
Co Sector	1	0.46	0.37	0.18	-0.023
Co Sector PRB	0.46	1	0.9	0.49	-0.026
Co Sector Max Users	0.37	0.9	1	0.37	-0.12
Co Sector Thpt	0.18	0.49	0.37	1	0.019
Availability	-0.023	-0.026	-0.12	0.019	1

***Figure 6**: Summary dashboard showing all insights*

Prior to the implementation of the hybrid model, the overall performance was assessed using the “TCMD” feature.

Figure 1 provides a comprehensive overview of the TCMD data, including its distribution, a box plot, a correlation matrix, and a categorical breakdown of performance. The distribution plot (Figure 1a) shows that TCMD values generally follow a normal distribution, though there is a slight skew to the right and a few outliers above +3. These outliers may represent unusually high values that could indicate performance issues or network bottlenecks. The box plot (Figure 1b) further highlights these outliers, reinforcing the possibility that certain network points are experiencing significant delays. The correlation matrix (Figure 1c) reveals a strong positive relationship between Co-Sector PRB Utilization and the number of maximum users (r = 0.9), suggesting that as more users connect, PRB utilization increases almost proportionally. In contrast, there is a moderate negative correlation between TCMD and Traffic (r = –0.49), indicating that higher traffic levels are generally associated with slower performance. Finally, the categorical breakdown (Figure 1d) shows that 44% of the data points are classified as Fair, 37.9% as Good, 9.8% as Excellent, and 8.3% as Poor, providing a snapshot of overall network performance.

Figure 2 presents the results of the performance analysis conducted across 845 TCMD network points. In Figure 2a, the TCMD values are plotted across all points, revealing a wide spread around the average (indicated by the dashed line). This distribution reflects varying levels of performance throughout the network, with some points significantly deviating from the normal. The central histogram (Figure 2b) introduces a more detailed view of this variability. Here, the red dashed line marks the 25th percentile at –0.5586, which serves as the threshold for identifying potential bottlenecks. A substantial number of data points fall at or below this level, highlighting areas of concern where performance degradation may be occurring. Figure 2c displays the distribution of network bottlenecks across three regions: Region A, Region B, and Region C. Each region reports an equal number of bottlenecks, with approximately 70 occurrences each. This uniform distribution suggests that network performance challenges are not localized but are spread across the monitored regions. This suggests that network performance challenges is not just a problem in a specific area, it occurs across all region. Overall, about 25.09% of the network is affected by these performance issues.

Figure 3 compares network performance before and after implementing the hybrid predictive model. The histograms in Figures 3a and 3b illustrate a noticeable leftward shift in TCMD values following the model's application, indicating an overall improvement in network performance. The scatter plot in Figure 3c compares actual versus predicted TCMD values, revealing a strong linear relationship and demonstrating the model's high predictive accuracy. Complementing this, the residual plot in Figure 3d shows residuals that are well-centred around zero, suggesting low bias and consistent model performance with minimal variance. Figure 3e presents a pie chart showing that 14.2% of previously identified bottlenecks were resolved after the model was applied, while the remainder persisted. Lastly, the bar chart in Figure 3f compares performance categories before and after the model's deployment. The results show a clear positive shift, with more network points now classified as Excellent or Good, and a reduction in the number rated as Fair or Poor. Collectively, these findings highlight the model's effectiveness in enhancing overall network performance and mitigating bottlenecks.

Figure 4 details how effective the model was at resolving network performance issues. The resolution matrix in Figure 4a shows that out of 43 identified bottlenecks, 30 were successfully resolved representing approximately 70%, while 13 remained unresolved. Figure 4b illustrates the distribution of performance improvements, which appears roughly centred with a slight skew to the right. This suggests that, in most cases, the model led to noticeable performance gains across the network. The "Top 50 Improvements" plot in Figure 4c highlights the network points with the most significant boosts in performance, offering clear targets for further optimization and refinement. Lastly, Figure 4d presents the model's resolution success rate by severity level: approximately 50% of high-severity issues were resolved, along with 80% of medium-severity and nearly all low-severity cases. These results indicate that the model is particularly effective at addressing low to moderate performance issues, with promising results even in more severe cases.

Figure 5 breaks down the key factors influencing network performance. The feature importance chart in Figure 5a highlights Traffic (GB), ERAB Setup Success Rate, and %R1 as the most impactful variables affecting TCMD. This is further supported by the correlation plot in Figure 5b, which shows that Traffic (GB) is negatively correlated with TCMD indicating that increased traffic is generally associated with slower performance. In contrast, Max Users and ERAB Setup Success Rate exhibit positive correlations with TCMD, suggesting that efficient user handling and higher connection success rates contribute to improved network performance. Figure 5c presents a scatter plot showing that network nodes with lower initial TCMD values tend to experience greater performance gains from the model, indicating that the model is particularly beneficial for underperforming areas. Lastly, the box plots in Figure 5d show a clear stepwise increase in TCMD across the performance categories Poor, Fair, Good, and Excellent. This pattern confirms that the classification thresholds used to group performance levels are logically defined and reflect meaningful differences in network behaviour.

Figure 6 consolidates all the key findings from the analysis. The Pie and bar charts in Figure 6a and 6b, reaffirm the earlier results indicating the improvement in model performance, showing a consistent distribution of performance classifications across the network. The model’s performance metrics ($R^2 = 0.74$, MSE = 0.187, MAE = 0.332) indicate strong predictive accuracy and reliability as shown in Figure 6c. The scatter plot in Figure 6d, indicates that many network nodes shifted above the bottleneck threshold after the model was applied, signalling successful improvements. The distribution chart in Figure 6e, shows a slight rightward skew in performance gains (mean = 0.016), consistent with earlier findings. The heatmap in Figure 6f, shows relationship between the various features. The regional analysis (Figure 6g) reveals the variation in network performance across three regions Rural, Urban, and Industrial. From the chart, the industrial region shows the highest positive improvement, indicated by the tall green bar, suggesting that network performance metrics such as throughput or availability were generally better in these areas. while the urban region shows a slight positive improvement, represented by the shorter blue bar, implying moderate network consistency and relatively stable conditions. In contrast, the rural region displays a negative value (red bar), indicating a decline in average performance compared to other regions. Overall, the chart suggests that industrial regions experienced stronger network performance, likely due to better infrastructure and higher resource concentration, while rural regions faced challenges such as limited coverage or capacity constraints. The time series chart (Figure 6h) shows a clear upward trend in performance over time especially in the final period suggesting that the model’s impact becomes more pronounced and measurable as time goes on.

4. CONCLUSION

The hybrid model delivers significant improvements to 4G LTE network performance, as showed by better TCMD values, reduced bottlenecks, and stronger performance classifications outcome. By evaluating results across different regions and over time, it's clear that machine learning driven strategies can deliver both localized fixes and broader network-wide gains. These findings support the case for wider deployment, with a focus on refining the model to better handle critical outliers and regional performance gaps.

Despite the model’s strong performance, there are several areas for further improvement. The rural region's underperformance suggests a need for region-specific retraining that accounts for local network conditions and user behaviour. Since the model's impact changes over time, incorporating time-series forecasting and seasonality could improve its predictive accuracy. To enhance interpretability, methods like SHAP or LIME could provide node-level insights, supporting more precise root-cause analysis. Expanding the model to include 5G performance indicators and data from multiple vendors would improve its scalability and generalizability. Finally, developing a real-time monitoring dashboard using tools like Streamlit or Power BI would allow operators to track, diagnose, and address network issues more effectively.

Superscripts

*	Corresponding author

Abbreviations

SVR	Support Vector Regressor
PRB	Physical Resource Block
FEM	Finite Element Method
HVAC	Heating, Ventilation, and Air Conditioning
SI	International System of Units
XRD	X-Ray Diffraction

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