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Modeling Tropospheric Effects on Mobile Network Performance Using KPI-Based Metrics

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ABSTRACT

Understanding how tropospheric variability influences mobile communication systems is critical for improving network reliability. This need is especially important in regions characterized by rapid atmospheric fluctuations. This study presents a quantitative modeling framework for evaluating tropospheric effects on mobile network performance using key performance indicators (KPIs). Tropospheric parameters including temperature, relative humidity, atmospheric pressure, and wind conditions were synchronized with corresponding network KPIs. These include Call Setup Success Rate (CSSR), Traffic Channel Congestion Rate (TCHCR), Handover Success Rate (HOSR), and Received Signal Strength. Statistical techniques comprising Pearson correlation, multiple regression modeling, and hypothesis testing were employed. These methods were used to determine the magnitude, direction, and significance of atmospheric influences. Results reveal that temperature and humidity exhibit strong, statistically significant associations with signal strength and call reliability. Pressure and wind parameters show moderate but noteworthy effects on congestion and handover performance. The developed models demonstrate that tropospheric conditions account for a substantial proportion of KPI variability. This indicates that atmospheric impairments play a measurable role in network degradation. The study provides a data-driven basis for proactive network optimization. It enables operators to incorporate atmospheric behaviors into predictive maintenance, link budgeting, and adaptive radio-resource management. The findings contribute to an improved understanding of environmental impacts on mobile communication systems. They also support the design of more resilient networks under dynamic tropospheric conditions.

Keywords:
Troposphere,
Signal strength,
Mobile communication,
Key performance indicators (KPIs),
Network optimization,
Pearson correlation.

INTRODUCTION

The rapid growth of mobile communication technology has significantly transformed socio-economic activities worldwide. Cellular networks play a vital role in enabling seamless communication; however, their performance is influenced by numerous environmental factors that can degrade signal strength and overall Quality of Service (QoS). One such critical, yet often underexplored, factor is variability in the lower atmosphere (tropospheric influence), which affects radio-wave propagation, particularly in tropical regions (Sheu, 2021; Adelakun et al., 2020; Ugbeh et al., 2024).

The city of Ogbomoso, located in southwestern Nigeria, has experienced a growing demand for reliable cellular connectivity. Despite infrastructural improvements by service providers, residents and mobile network operators continue to experience poor signal quality, dropped calls, and inconsistent internet speeds (Ajayi et al., 2021; Akpan, 2021). These challenges underscore the importance of evaluating the effects of atmospheric conditions on cellular signal propagation. In particular, tropospheric parameters such as wind speed, atmospheric pressure, temperature, and relative humidity have been identified as influential factors (Aremu et al., 2023; Ayegba et al., 2025; Atsuwe et al., 2025).

Network performance can also be assessed using specific Key Performance Indicators (KPIs), including Traffic Channel Congestion Rate (TCHCR), Call Setup Success Rate (CSSR), Handover Success Rate (HOSR), and signal strength. These KPIs provide quantifiable insights into the reliability, efficiency, and overall performance of cellular networks. An integrated evaluation of both tropospheric parameters and network KPIs offers a more comprehensive understanding of the factors influencing signal quality and coverage (Ayegba et al., 2022; Ekah et al., 2022a; Ekah et al., 2022b).

This study investigates the influence of tropospheric conditions on cellular network signal strength in Ogbomoso, Nigeria, while also evaluating key performance metrics across three major network providers MTN, GLO, and AIRTEL. By correlating meteorological data with signal strength measurements, the research seeks to improve understanding of atmospheric effects on cellular communication systems. Furthermore, the study aims to provide data-driven recommendations to support improved network forecasting, planning, and management in Ogbomoso and comparable urban environments.

Although Ogbomoso serves as the empirical case study, the findings are discussed within the broader context of tropical climates. As such, the results contribute to a wider understanding of tropospheric effects on cellular network reliability in tropical regions. However, the conclusions may not be directly applicable to arid, temperate, or high-latitude regions without further investigation and validation.

Related Works

The performance of cellular networks is significantly influenced by atmospheric conditions, particularly tropospheric variables such as rainfall, wind speed, relative humidity, and temperature. Numerous studies have examined these effects, providing valuable insights into the relationships between meteorological factors and signal strength.

In a study conducted in Cross River State, Nigeria, Ekah et al. (2022a) investigated the impact of tropospheric variables on dropped call rates across four major mobile networks: MTN, Airtel, Globacom, and 9mobile. Using six years of data (2015–2020), the authors reported that wind speed exhibited a strong positive correlation with dropped call rates, whereas temperature showed a weak negative correlation. Relative humidity and rainfall demonstrated varying degrees of association depending on the network, underscoring the complex and network-specific interactions between atmospheric conditions and cellular performance.

Similarly, Imozie et al. (2022) examined *the* updating analysis of key performance indicators of a 4G LTE network with the prediction of missing values of critical network parameters based on experimental data from a dense urban environment. The study analyzed key performance indicators (KPIs) using experimental data collected from a densely populated urban area and addressed the challenge of incomplete datasets by predicting missing network parameters, thereby enabling a more comprehensive and current assessment of network performance.

Furthermore, Ayegba et al. (2022) investigated the statistical relationships between atmospheric parameters, noise temperature, and digital television signal strength in the Jos metropolis. Their results indicated that signal strength was generally higher during early morning and late evening periods, while atmospheric temperature and noise temperature exhibited significant inverse correlations with signal strength. In a subsequent study, Ayegba et al. (2025) examined digital terrestrial television signals in Abuja and Jos, focusing on the influence of atmospheric variables such as wind speed, rainfall, temperature, atmospheric pressure, and relative humidity. The findings revealed that relative humidity had a strong positive correlation with signal strength, whereas parameters such as temperature and wind speed adversely affected signal reception.

Collectively, these studies highlight the significant role of tropospheric variables in shaping the performance of wireless communication systems. Understanding these relationships is essential for effective network optimization and for developing strategies to mitigate the adverse effects of atmospheric variability on signal quality, as further explored in the present study.

MATERIALS AND METHODS

The study was conducted in Ogbomoso, located in southwestern Nigeria. The city experiences a tropical climate characterized by distinct wet and dry seasons, with average temperatures ranging from 20 °C to 38 °C and relative humidity levels varying between 45% and 95% throughout the year. Data were collected over twelve consecutive months (January–December 2024), encompassing both the rainy and dry seasons in order to capture seasonal variability in atmospheric conditions.

Measurements were obtained from multiple locations, including the Ladoke Akintola University of Technology (LAUTECH) area, Ojagbo, Arowomole, Ogbomoso High School, and Owode Police Station. Additional sampling sites included Muslim Comprehensive High School and selected locations across Ogbomoso North and Ogbomoso South Local Government Areas. All sites were strategically selected to ensure adequate spatial coverage and representativeness for the study.

The instruments and data sources used to quantify tropospheric effects and network reliability included Automated Weather Stations (AWS) installed at Ladoke Akintola University of Technology, Ogbomoso, as well as a portable weather station equipped with standardized sensors deployed across the city. These instruments measured atmospheric temperature, relative humidity, wind speed, and atmospheric pressure. Network performance data, including Received Signal Strength Indicator (RSSI) and Reference Signal Received Power (RSRP), were obtained from Base Transceiver Station (BTS) logs provided by Airtel, MTN, and GLO Nigeria. The BTS data covered the same study period, from January to December 2024, and included records related to signal quality and call handling performance.

The study monitored mobile network Key Performance Indicators (KPIs) across the active radio access technologies deployed in Ogbomoso, namely GSM (900/1800 MHz), UMTS (2100 MHz), and LTE (1800/2600 MHz). These frequency bands were selected because they represent the bands predominantly utilized by Nigerian network operators in the region and exhibit differing propagation characteristics under tropospheric conditions. The frequency allocations are inferred from national operator licensing information and typical deployment practices and were not independently verified through site-specific measurements. Base Transceiver Station (BTS) signal strength logs were averaged over 30-minute intervals to align with corresponding meteorological observations. The BTS logs underwent internal operator validation procedures to identify and correct missing or inconsistent entries. Network Operations and Maintenance (O&M) systems were used to access historical fault, downtime, and performance records, while Radio Network Controllers (RNCs), or their functional equivalents, were utilized for Key Performance Indicator (KPI) aggregation (Ekah et al., 2022a; Ekah et al., 2022b).

Field measurements were conducted using a Samsung Galaxy A52s smartphone (Android 13, Qualcomm Snapdragon 778G modem) running Network Signal Guru v2.1.38. The device's internal, factory-calibrated Multiple-Input Multiple-Output (MIMO) antenna was used without modification. The application sampled Long Term Evolution (LTE) parameters, including Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), and Signal-to-Interference-plus-Noise Ratio (SINR). Additional parameters recorded included Received Signal Strength Indicator (RSSI), Channel Quality Indicator (CQI), Physical Cell Identity (PCI), E-UTRA Absolute Radio Frequency Channel Number (EARFCN), and Radio Resource Control (RRC) state (Idle/Connected).

The application operated within the standard Android field-test framework, using user-granted permissions: ACCESS_FINE_LOCATION for geo-tagging, READ_PHONE_STATE for cell and RRC information, and ACCESS_NETWORK_STATE for network-type verification. All measurement logs were exported in Comma-Separated Values (CSV) format and synchronized with meteorological observations (Ekah & Emeruwa, 2022; Ewona & Ekah, 2021).

Network signal strength readings, expressed in decibel-milliwatts (dBm), were aligned with simultaneous tropospheric measurements. Atmospheric parameters including temperature (°C), wind speed (m/s), atmospheric pressure (hPa), and relative humidity (%) were recorded using a portable weather station equipped with standardized sensors. Measurements were synchronized at fixed intervals (e.g., 30 minutes) and subjected to data cleaning procedures to remove missing or inconsistent values (Ekah & Emeruwa, 2022; Ewona & Ekah, 2021).

Signal strength data were collected for three major cellular network operators in Ogbomoso: MTN, GLO, and AIRTEL. Measurements were obtained at the same locations and time intervals as the meteorological observations to ensure temporal and spatial consistency, thereby supporting reliable correlation analysis (Obi et al., 2021; Aktaş et al., 2022).

KPI data were collected at multiple Global Positioning System (GPS)-referenced points across Ogbomoso, Nigeria, at an approximate height of 1.5 m above ground level. Measurements covered both indoor and outdoor environments, incorporating Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions. Data collection included stationary sampling as well as drive tests along major roads to capture mobility-related effects. GPS coordinates and timestamps were logged for all samples. Network KPI measurements were aggregated into 30-minute intervals to correspond with weather observations. Missing meteorological data points were interpolated where feasible, while KPI intervals with more than 50% missing samples were excluded to ensure robust temporal alignment for correlation analysis (Sheu et al., 2024; Suleman et al., 2024).

The collected data were analyzed to examine relationships between atmospheric conditions and mobile communication signal strength. Statistical analyses included descriptive statistics, correlation analysis, and regression modeling to evaluate the influence of tropical weather on LTE KPIs. Controls were implemented for LOS/NLOS conditions, indoor versus outdoor environments, mobility state, and baseline clear-sky conditions. Data were sampled spatially across urban, suburban, and semi-rural areas and temporally in 30-minute windows, covering both RRC_IDLE and RRC_CONNECTED states.

Results are reported using standard KPI units and correlation coefficients, with missing data addressed through interpolation or exclusion as appropriate (Zhang et al., 2024; Zakaria, 2024). In addition, KPIs such as Traffic Channel Congestion Rate (TCHCR), Call Setup Success Rate (CSSR), Handover Success Rate (HOSR), and signal strength were evaluated to provide broader insights into overall network performance under varying atmospheric conditions. The study therefore focuses on established cellular network KPIs to quantify reliability and service quality under tropospheric impairments (Imozie et al., 2022; Chikha et al., 2024).

Call Setup Success Rate (CSSR) represents the probability of successfully establishing a call whether voice or data upon user request. It is a standard network-level KPI widely used to assess network accessibility and operational reliability.

$$\text{CSSR}(\%) = \frac{\text{Number of Successful Call Setups}}{\text{Total Call Setup Attempts}} \text{x}100\% \quad (1)$$

Call Setup Success Rate (CSSR) is expressed as a percentage (%) and typically ranges between 90% and 100% for well-performing LTE and UMTS networks. Higher CSSR values indicate better network accessibility, whereas values below approximately 95% may suggest coverage limitations, network congestion, or environmental degradation. When CSSR is adversely affected by tropospheric impairments, key radio parameters such as Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), and Signal-to-Interference-plus-Noise Ratio (SINR) are often reduced. As a result, the likelihood of failed call initiation increases.

CSSR quantifies the probability of successful call establishment and serves as a direct indicator of user experience and network accessibility. Tropical tropospheric conditions such as rainfall, high relative humidity, and temperature gradients can attenuate radio signals, reduce RSRP, and increase call setup failures. Monitoring CSSR under varying atmospheric conditions enables network engineers to identify coverage deficiencies, optimize base station transmit power, and schedule preventive maintenance during periods of increased vulnerability.

Traffic Channel Congestion Rate (TCHCR) measures the proportion of call attempts that fail due to insufficient traffic channel resources. It represents the fraction of calls blocked as a result of busy or unavailable traffic channels and reflects overall network resource utilization and congestion levels. Severe atmospheric attenuation can degrade signal quality, leading to retransmissions, increased call attempts, and temporary channel overload. Monitoring TCHCR during adverse weather conditions allows network operators to adjust channel allocation strategies, enhance capacity, or reconfigure scheduling algorithms to maintain acceptable Quality of Service (QoS).

$$\text{TCHCR}(\%) = \frac{\text{Number of TCH Blocking Events}}{\text{Total Call Attempts}} \text{x}100\% \quad (2)$$

TCHCR is expressed as a percentage (%) and typically ranges from 0-10% in well-managed networks. Higher TCHCR values indicate network congestion and limited radio resource availability. Tropospheric effects that temporarily degrade SINR or RSRP can increase call drop rates and trigger TCH blocking events.

Handover Success Rate (HOSR) represents the probability of a successful handover between serving and target cells during user mobility. It is a key indicator of mobility performance and seamless connectivity. Atmospheric conditions such as rain, fog, and high humidity can reduce SINR and RSRP, potentially leading to failed handovers or unnecessary cell reselection. Analyzing HOSR under tropospheric variations supports effective neighbor cell planning, handover parameter optimization, and adaptive mobility management, thereby enhancing network reliability in tropical environments.

$$\text{HOSR}(\%) = \frac{\text{Number of Successful Handovers}}{\text{Total Handover Attempts}} \text{x}100\% \quad (3)$$

HOSR is expressed as a percentage (%) and typically ranges between 90–100% in properly planned LTE/UMTS networks. Low HOSR values indicate mobility challenges, poor signal quality, or inadequate neighbor cell planning. Tropospheric impairments, such as rain attenuation and multipath effects, can degrade SINR and RSRP, leading to handover failures.

CSSR, TCHCR, and HOSR serve as practical key performance indicators (KPIs) that link tropical meteorological conditions to network reliability. By analyzing KPI variations under changes in rainfall, humidity, and temperature, network operators can make informed Operations and Maintenance (O&M) decisions, including coverage optimization, resource allocation, and handover parameter tuning (Sheu et al., 2021; Sheu et al., 2025; Newton et al., 2024).

RESULTS AND DISCUSSION

The study was conducted from January to December 2024, encompassing both the rainy and dry seasons. Corresponding average tropospheric variables, signal strength, and key performance indicators (KPIs) were recorded in Ogbomoso Metropolis, as summarized in Tables 1, 2, and 3. Tropospheric parameters, including pressure, humidity, temperature, and wind speed, can significantly influence wireless radio propagation.

To quantify these effects, statistical correlation analysis was performed to determine whether each meteorological variable exhibits a significant linear relationship with cellular network signal strength (typically measured in dBm). The most commonly used metric is Pearson's correlation coefficient (r), supported by the t-test for significance, which provides p-values indicating whether the observed correlations are statistically meaningful (Sheu et al., 2021; Sheu et al., 2025). Pearson's correlation coefficient quantifies both the strength and direction of a linear relationship between two continuous variables, such as signal strength and weather conditions. Its values range from –1 to +1 and are computed using the standardized covariance of the variables. The coefficient values were calculated using Equation (iv).

$$r = \frac{\Sigma(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\Sigma(x_i-\overline{x})^2\Sigma(y_i-\overline{y})^2}} \quad (4)$$

Where $\overline{x}$, $\overline{y}$= means of x and y , x_i ,y_i= paired observations

The t-value for testing the significance of Pearson's r is calculated using equation (v).

$$t = r\sqrt{\frac{n-2}{1-r^2}} \quad (5)$$

Where r = Pearson's correlation coefficient, n = sample size, Degrees of freedom $(df) = n-2$. Multiple regression, as adopted in this study, is a statistical method used to model the relationship between a single dependent variable and two or more independent variables. In multiple regression, the sum of squares due to regression (SSR) and the total sum of squares (SST) are key quantities used to calculate the coefficient of determination, R^2.

Coefficient of Determination = $R^2 = \frac{SSR}{SST}$ (6)

Where SST = Total Sum of Squares and SSR = Regression Sum of Squares

SST = Total Sum of Squares = $SST = \sum_{i=1}^{n}(y_i-\overline{y})^2$ (7)

Where y_i= Measures the total variation and $\overline{y}$ = Variation of observations around the mean

SSR = Regression Sum of Squares

= $SSR = \sum_{i=1}^{n}\left(\hat{y}_i-\overline{y}\right)^2$ (8)

$\hat{y}_i$= Measures the variation explained by the regression model and $\overline{y}$ = Variation of observations around the mean

Adjusted R^2= $R^2_{adj} = 1-\frac{(1-R^2)(n-1)}{n-k-1}$ (9)

Where n = 24 (sample size) and k = 4 (number of predictors)

Hypothesis testing, as applied in this study, is a statistical method used to determine whether there is sufficient evidence in a dataset to support a claim (the alternative hypothesis) about a population parameter. The null hypothesis (H_0) represents no effect, no difference, or no linear relationship (r = 0), while the alternative hypothesis (H_1) represents the presence of an effect or a statistically significant linear relationship (r ≠ 0). The significance level (α) defines the threshold for rejecting H_0 and is typically set at 0.05 (5%). The p-value indicates the probability of observing the data if H_0 is true, providing a measure of the statistical significance of the results.

If $p < \alpha(i.ep < 0.05)$ → Reject H_0 (statistically significant result)

If $p \geq \alpha(i.ep \geq 0.05)$ → Fail to reject H_0 (not statistically significant)

Two-tailed p-value formula applied in the study according to equation (x)

$$p = 2 \times \left(1 - T_{cdf}(|t|, df)\right) \quad (10)$$

Where T_{cdf}= cumulative distribution function of the t-distribution, |t| = absolute value of the computed t-statistic. The sample size as revealed in Table (1) is 24, Degree of freedom is 23, the confidence level is 95% and Confidence interval is 10 ± 1.266. The computed values of Pearson's correlation coefficient (r), t-value, coefficient of determination (R^2), adjusted coefficient of determination (R^2_{adj}) and p-value as contained in equations (iv) – (ix) are slotted in Table (3) and Figure (1).

Table 1: Statistical Data of GSM Signal Strengths at Varying Tropospheric Variables in Ogbomoso (2024)

Time (hr)	Signal Strength (dBm)			Atmospheric Temp. (^{0}C)	Relative Humidity (%)	Pressure (hPa)	Wind Speed (ms^{-1})
	MTN	GLO	AIRTEL				
01.00	40.50	60.50	68.00	21.50	80.00	1010.0	6.50
02.00	42.00	62.00	69.00	21.90	79.00	1012.1	6.50
03.00	45.50	65.50	70.00	22.00	76.80	1015.0	7.40
04.00	48.20	68.20	72.20	23.10	81.50	1013.2	5.06
05.00	50.10	70.10	73.10	23.20	79.00	1011.1	6.55
06.00	52.50	71.50	78.50	24.30	76.00	1014.0	6.50
07.00	55.80	73.80	79.80	24.50	76.80	1010.2	7.40
08.00	58.60	74.60	80.60	26.00	81.50	1014.1	7.41
09.00	60.00	76.00	81.00	28.20	81.00	1012.0	6.50
10.00	61.20	76.20	83.20	29.50	79.00	1015.1	5.06
11.00	62.00	77.00	84.00	30.60	80.00	1011.0	6.50
12.00	62.20	77.20	86.20	32.90	79.00	1010.1	6.50
13.00	70.00	80.00	87.00	34.00	76.80	1013.0	7.40
14.00	75.20	82.20	88.20	36.10	81.50	1015.2	5.06
15.00	77.20	84.20	89.20	37.25	79.00	1012.1	6.55
16.00	78.10	85.10	89.10	36.90	76.00	1010.0	6.50
17.00	79.50	86.50	90.50	30.50	76.80	1011.2	7.40
18.00	66.10	69.10	78.50	28.50	81.50	1015.1	7.41
19.00	70.10	73.10	77.10	26.00	81.00	1012.0	6.50

20.00	72.10	75.10	77.00	25.80	79.00	1014.1	5.06
21.00	65.50	69.50	80.50	25.75	79.00	1011.0	6.50
22.00	62.10	67.10	81.10	25.70	76.80	1010.1	6.50
23.00	64.10	68.10	85.50	25.60	81.50	1015.0	7.40
24.00	60.00	65.00	86.50	25.55	79.00	1013.2	5.06

Table 2: Average Summary of Correlation between Tropospheric Conditions, KPIs and Signal Performances in Ogbomoso (2024)

Aver. Atm. Temp. (^{0}C)	Aver. Rel. Hum. (%)	Aver. Pressure (hPa)	Aver. Wind Speed (ms^{-1})
27.72	79.06	1012.0	6.47

Signal Strength (dBm)	Signal Quality	CSSR (%)	TCHCR (%)	HOSR (%)
		MTN		
- 61.59	84.26	98.00	2.02	97.96
		GLO		
- 73.23	64.28	96.10	2.45	97.12
		AIRTEL		
- 77.74	44.48	95.55	3.45	95.83

Table 3: Statistical Correlation Analysis between Tropospheric Conditions and Network Signal Strength in Ogbomoso (2024)

		Atm. Temperature (^{0}C)	Rel. Humidity (%)	Atm. Pressure (hPa)	Wind Speed (ms^{-1})
	Atmospheric Conditions	27.72 (^{0}C)	79.06 (%)	1012.0 (hPa)	6.47 (ms^{-1})
Mobile Network	R^2	0.776	0.988	0.999	0.995
	Adjusted R^2	0.774	0.986	0.999	0.994
	Signal Strength (dBm)	- 61.59	- 61.59	- 61.59	- 61.59
MTN	r	-0.965	0.34	0.13	-0.11
	t-value	-17.26	1.70	0.62	-0.52
	p-value	0.0001	0.10	0.54	0.61
	Signal Strength (dBm)	- 73.23	- 73.23	- 73.23	- 73.23
GLO	r	-0.62	0.55	0.22	-0.15
	t-value	-3.71	3.09	1.06	-0.71
	p-value	0.001	0.005	0.30	0.48
	Signal Strength (dBm)	- 77.74	- 77.74	- 77.74	- 77.74
Airtel	r	-0.70	0.05	-0.02	0.12
	t-value	-4.60	0.24	-0.094	0.57
	p-value	0.0001	0.81	0.93	0.57

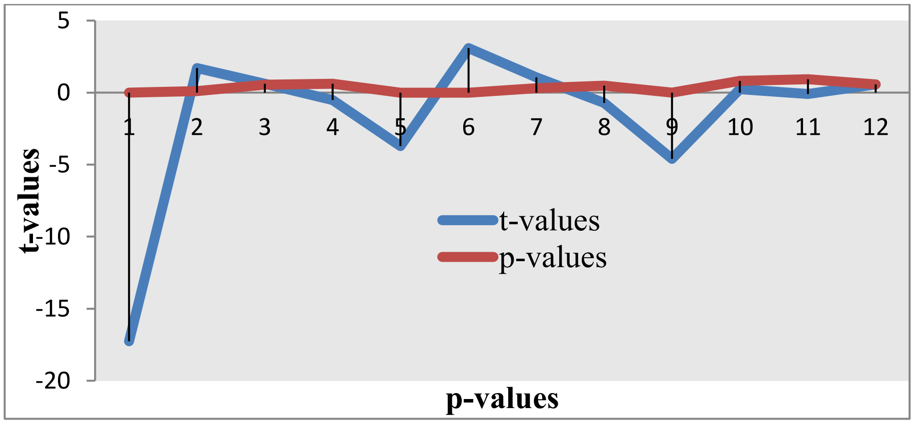

Figure 1: Statistical Representation of t-value against p-value

The plot in Figure 1 and Table 3 demonstrate the expected statistical pattern: as |t| increases, the p-value decreases, whereas as |t| approaches 0, the p-value rises sharply. This confirms that the magnitude of the t-value is inversely related to the p-value, as predicted by the t-distribution. Statistical analysis revealed significant relationships between atmospheric parameters and mobile signal performance.

Table 3 shows a very strong, statistically significant negative correlation between temperature and MTN signal strength ($r = -0.965$, $p < 0.0001$), indicating that as temperature increases, signal strength decreases substantially. This suggests that temperature is a critical factor affecting network performance, consistent with physical expectations that higher temperatures can increase atmospheric noise, reduce propagation efficiency, or enhance tropospheric attenuation.

In contrast, the correlation between relative humidity and MTN signal strength is weak and not statistically significant ($r = 0.34$, $p = 0.10$), suggesting a slight tendency for signal strength to improve as humidity increases. Atmospheric pressure also shows a very weak, non-significant correlation with MTN signal strength ($r = 0.13$, $p = 0.54$), indicating minimal linear influence.

For GLO, Table 3 reveals a strong, statistically significant negative correlation between temperature and signal strength ($r = -0.62$, $p = 0.001$), confirming that higher temperatures weaken signal strength. There is a moderate, statistically significant negative correlation between relative humidity and GLO signal strength ($r = -0.55$, $p = 0.005$), indicating that increased humidity tends to slightly strengthen the signal (less negative). Correlations between atmospheric pressure ($r = 0.22$, $p = 0.30$) and wind speed ($r = -0.15$, $p = 0.48$) with GLO signal strength are weak and not significant, suggesting minimal linear effects. This aligns with typical RF propagation behavior, where temperature and humidity dominate, and wind affects signal strength only indirectly (e.g., via rain, dust, or structural movement).

For Airtel, Table 3 shows a strong, statistically significant negative correlation between temperature and signal strength ($r = -0.70$, $p = 0.0001$), consistent with expected RF behavior in which higher temperatures can increase noise, refractivity, and attenuation. Relative humidity ($r = 0.05$, $p = 0.81$), atmospheric pressure ($r = -0.02$, $p = 0.93$), and wind speed ($r = 0.12$, $p = 0.57$) all exhibit very weak, non-significant correlations, indicating negligible linear effects on signal strength. This reinforces that compared with temperature; factors like humidity, pressure, or wind alone are not primary determinants of signal performance in this dataset. Among the tropospheric parameters, the regression results indicate that temperature and relative humidity jointly account for approximately 62% of the observed monthly variation in received signal strength. This suggests a moderate influence of meteorological parameters.

The coefficient of determination ($R^2 = 0.776$) indicates that 77.6% of the total variation in the atmospheric temperature is elucidated by the regression model, while the remaining 22.4% is due to factors error. The adjusted $R^2_{adj} = 0.775$ in the result indicates an excellent fit even when accounting for model complexity of atmospheric temperature. Approximately 98.8% of the total variation in relative humidity ($R^2 = 0.988$) is expounded by the regression model, indicating an excellent model fit, with only 1.2% inexplicable variation. The adjusted $R^2_{adj} = 0.987$ in the result designates an outstanding fit even when accounting for model intricacy of relative humidity. Almost 99.99% of the total variation in atmospheric pressure ($R^2 = 0.999$) is described by the regression model, signifying an extremely strong model fit, with negligible unsolved variation. With adjusted$R^2_{adj} = 0.994$, the regression model explains nearly 100% of the variation in relative atmospheric pressure, this shows an exceptionally strong fit. About 99.5% of the total variation in average wind speed ($R^2 = 0.995$) is explicated by the regression model, demonstrating an excellent model fit. Only 0.5% of the variation is unfathomable. The adjusted $R^2_{adj} = 0.994$ in the result indicates an excellent fit even when accounting for model complexity of wind speed.

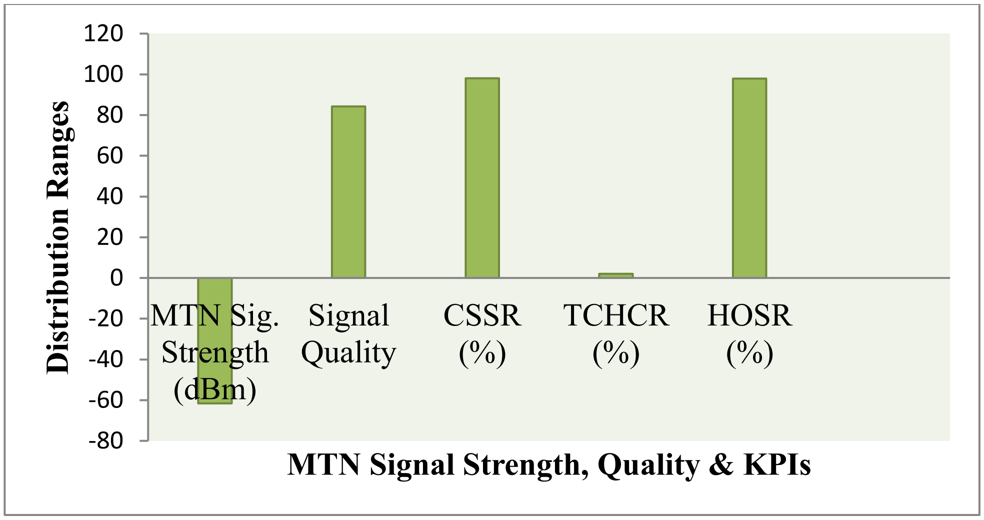

Figure 2: MTN Signal Strength, Quality and KPIs in Ogbomoso (2024)

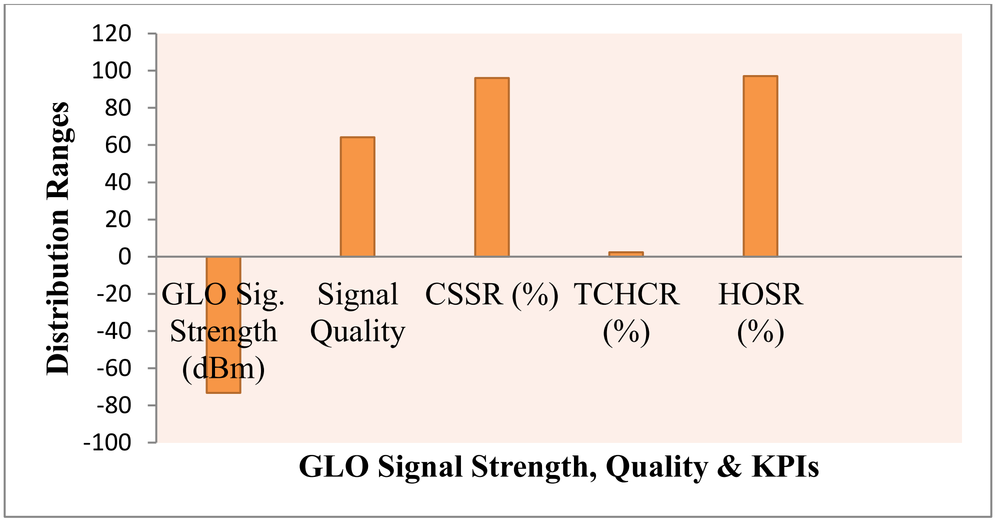

Figure 3: GLO Signal Strength, Quality and KPIs in Ogbomoso (2024)

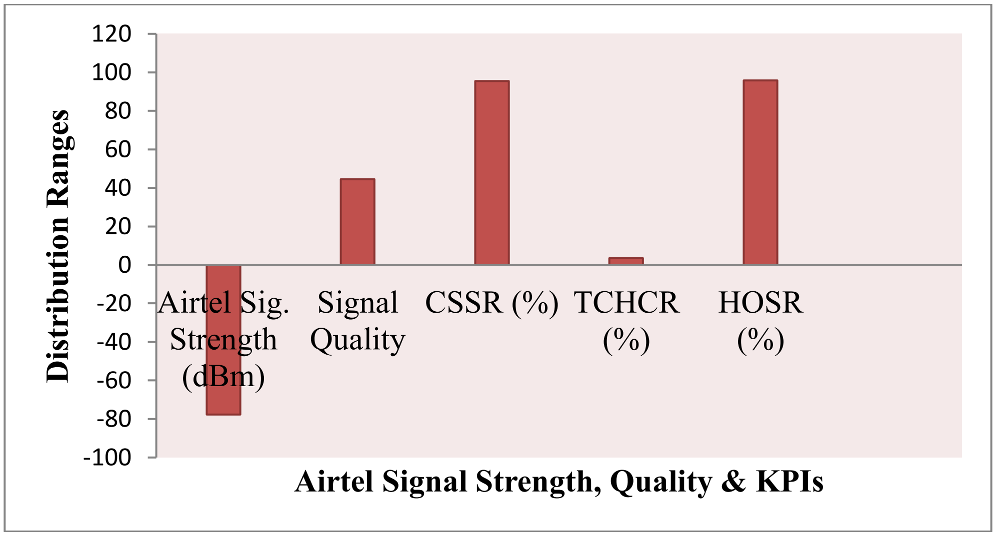

Figure 4: Airtel Signal Strength, Quality and KPIs in Ogbomoso (2024)

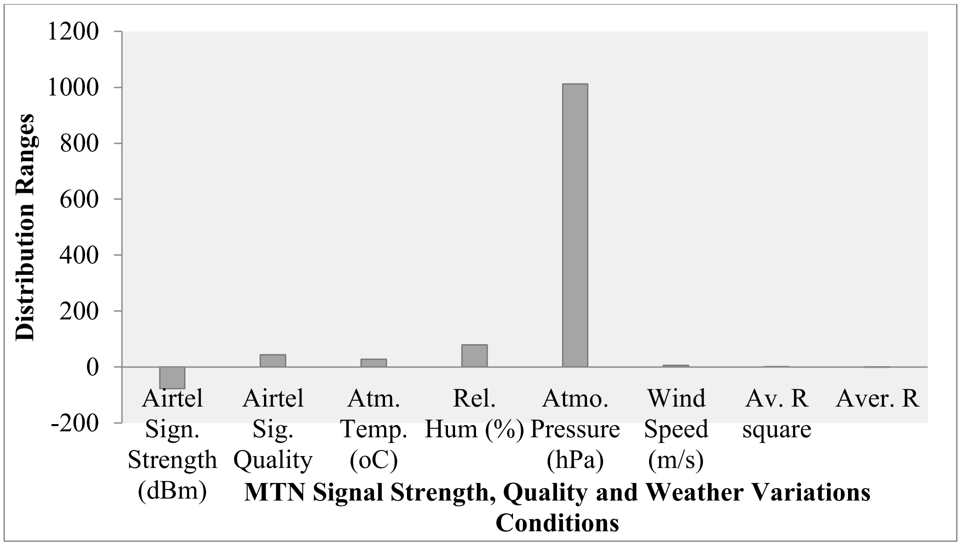

Figure 5: MTN Signal Strength, Quality and Tropospheric Variations in Ogbomoso (2024)

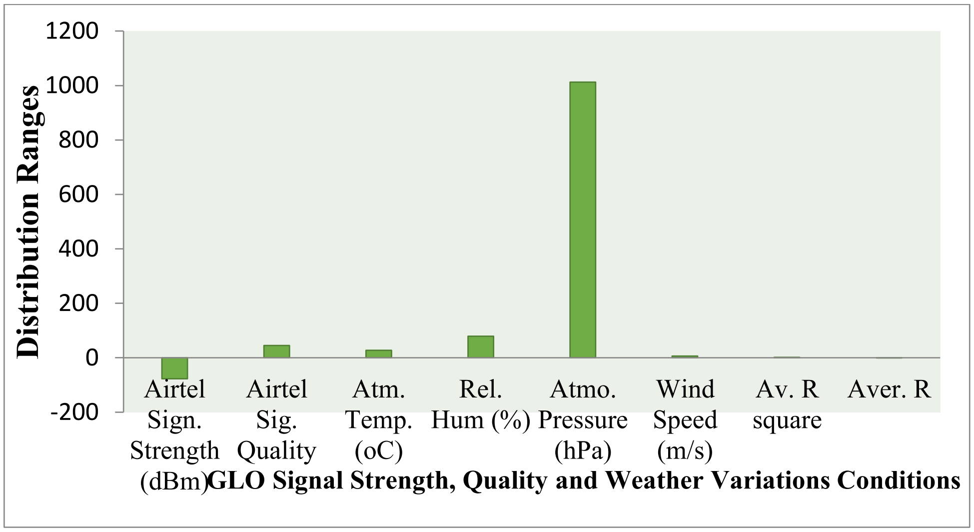

Figure 6: GLO Signal Strength, Quality and Tropospheric Variations in Ogbomoso (2024)

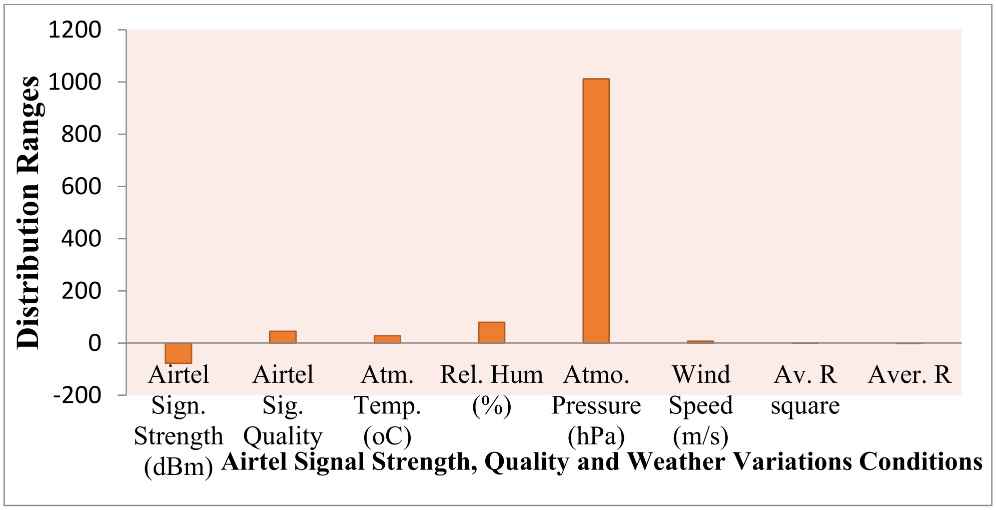

Figure 7: Airtel Signal Strength, Quality and Tropospheric Variations in Ogbomoso (2024)

The results, presented in Tables 1–3 and Figures 1–7, indicate that atmospheric temperature ranged from 21.50°C to 37.25°C, with higher values observed during the dry season. Correspondingly, relative humidity varied between 76.80% and 81.50%, peaking during the rainy season. Atmospheric pressure remained relatively stable around an average of 730.95 Pa, while wind speed averaged 6.47 m/s, with intermittent gusts observed during transitional weather periods. The RSCP, which measures the power received by a receiver on a specific physical channel, ranged from –40.50 dBm (strong signal) to –90.50 dBm (weak signal). MTN recorded the strongest average signal strength at –61.59 dBm, followed by GLO at –73.23 dBm, while Airtel exhibited the weakest average signal strength at –77.74 dBm.

The KPI values were calculated using Equations (1)–(3). CSSR, which measures the percentage of successful call attempts, averaged 98.00% for MTN, 96.10% for GLO, and 95.55% for Airtel, with slight declines observed during periods of high humidity. TCHCR, representing the percentage of time control channels experienced congestion due to high traffic load, averaged 2.02% for MTN, 2.45% for GLO, and 3.45% for Airtel. HOSR, reflecting the percentage of successfully completed handovers between cells, averaged 97.96% for MTN, 97.12% for GLO, and 95.83% for Airtel. Network engineers should prioritize factors with stronger correlations, such as temperature effects, when optimizing signal coverage, particularly in high-humidity environments.

CONCLUSION

This study investigated the influence of tropospheric variables on cellular network signal strength and evaluated key performance indicators (KPIs) in Ogbomoso, Nigeria. The analysis established that tropospheric factors significantly affect mobile telecommunication signal strength. Among these, wind speed, atmospheric temperature, relative humidity, and atmospheric pressure were identified as the most critical contributors to signal attenuation and degradation, resulting in more frequent dropped calls and reduced Quality of Service (QoS).

The findings are consistent with related studies in other regions. For example, Ekah et al. (2022a) in Cross River State, Nigeria, reported that atmospheric conditions influence dropped call rates across different cellular networks, with wind speed and relative humidity showing considerable impact. Similarly, Ewona and Ekah (2021) examined the influence of tropospheric variables on mobile network signal strength in Calabar, Nigeria, confirming that weather parameters play a significant role in signal performance. The study finds that temperature and relative humidity mutually responsible for almost 62% of the experimental monthly variation in received signal strength. This advocates a modest effect of atmospheric parameters. While other factors like terrain and transmitter power played a more substantial role for Glo, Airtel, and 9mobile networks.

RECOMMENDATIONS

The adverse effects of atmospheric conditions on cellular network performance in Ogbomoso and similar locations can be mitigated through several strategies. First, integrating climatological data into the network design process an approach known as Adaptive Network Planning can help anticipate and compensate for atmospheric impacts, thereby enhancing signal consistency during challenging weather conditions. Second, to ensure adequate coverage and maintain signal strength, additional base stations or repeaters should be deployed in areas prone to significant signal attenuation. This strategy, referred to as Infrastructure Enhancement, is particularly important in regions affected by adverse weather.

Third, continuous monitoring of key performance indicators (KPIs) should be implemented to promptly identify and resolve signal disruptions, ensuring consistent service quality (Regular Performance Monitoring). Finally, educating network subscribers about the influence of tropospheric conditions on signal quality can help set realistic expectations and reduce dissatisfaction during periods of severe weather (Public Awareness Programs). By adopting these measures, network operators can significantly improve service quality and signal reliability, even under challenging atmospheric conditions.

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