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Temporal Trends, Inequality and Forecasting of ISP Latency in Nigeria, 2020–2023

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Abstract
Internet Service Providers (ISPs) experience variability and inequality in network latency, affecting service quality and user experience. This study addresses assessment of latency performance by quantifying trends, inequality, regime changes, and forecasting behaviour across ISPs. Monthly latency measurements collected from January 2020 to December 2023 were cleaned by removing zero and negative observations and summarised using descriptive statistics. Gini and Theil indices and Lorenz curves quantified latency inequality, while seasonal-trend decomposition and Augmented Dickey-Fuller test examined behaviour and stationarity. A two-state Markov-switching autoregressive model classified network conditions into "good" and "bad" regimes. ARIMA, Holt-Winters, Prophet and Random Forest models were evaluated using CRPS and pinball loss metrics. Mean latency ranged from 8.04 ms for Dimension Data to 32.73 ms for InqDigital. Random Forest achieved the best performance. The study demonstrates that combining inequality analysis, regime classification and machine-learning forecasting can support early identification of elevated latency and stable ISP QoS.

Keywords: Internet latency, internet service providers, latency inequality, random forest, forecasting

INTRODUCTION

In the digital society that we live in, internet is utilized by business owners, educators, health care personnel and the media industries and it is of paramount importance to the provision of reliable connectivity and quality of service (QoS) through the use of Internet Service Providers (ISPs) (Nzobokela et al., 2024). One of the QoS metrics that seems to have significant importance is latency, the delay between a request made by a person to the server and a response coming back to that person in real-time applications like video calls, video gaming and VoIP (Megat et al., 2024).

Another impact is that high or variable latency can cause interrupted services and low-quality user experience, which may be unacceptable to businesses in many instances and requires ISPs to manage latency effectively in locations with well-defined and maintained infrastructure while having to deal with network congestion in other cases. The level of variability and inequality among different Internet Service Providers is more evident in developing economies, where differences in infrastructure coverage, irregularity in service quality and relatively weak regulatory environments may contribute to disparities in service performance. This latency gap provides an unequal experience to users because some subscribers experience poor connection speeds and discontinued online communication. In addition, unreliable service performance may also stem from sporadic increases in latency or congestion. It is thus important to effectively understand these latency patterns in order to enhance the quality of the internet and support evidence-based policymaking by operators and regulators.

Existing studies have examined network latency, quality of service, network monitoring and forecasting from different perspectives. Some studies have focused on latency measurement

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AFRICA HABITAT REVIEW 21(3) 2026

and network performance, while others have examined statistical and machine-learning techniques for analysing and forecasting network behaviour (Komosny, 2022; Saflor et al., 2024). However, much of this research has tended to examine average latency, monitoring approaches or individual predictive techniques separately. Limited attention has been given to an integrated assessment combining temporal trends, seasonal behaviour, inequality in ISP latency, regime changes and comparative forecasting performance, particularly within the Nigerian ISP context.

This paper therefore examines trends in latency rates among several ISPs in Nigeria over a period of years by using a multi-stage procedure composed of descriptive statistics, measures of inequality through Gini and Theil indices, time-series modelling and machine learning. The Markov-switching model is used to identify dynamic changes between relatively good and poor latency regimes, providing indications of periods of deterioration and recovery. To conduct forecasting, four models are considered: ARIMA, Holt-Winters, Prophet and Random Forest.

The strength of this contribution is providing a multi-stage approach to latency modelling and forecasting, which combines descriptive analysis, inequality measures, regime-switching models and predictive approaches. Unlike traditional QoS research whose key topic is often average latency, the paper gives precedence to measuring disparities in ISP performance while also identifying underlying structural changes in network conditions. The study further examines the predictive performance of statistical and machine-learning approaches within the heterogeneous environment of Nigerian ISPs. Contextualized within Nigeria's infrastructural setting, the findings are intended to provide insights for ISPs, regulators and policymakers committed to improving service quality and ensuring equitable internet access.

Aim and Objectives of the Research

This research aims to analyse temporal trends and inequalities in ISP latency in Nigeria and compare the forecasting performance of selected statistical and machine-learning models.

The objectives are to:

i. Examine the distribution and variability of latency among selected Nigerian Internet Service Providers.
ii. Determine temporal trends and seasonal patterns in ISP latency between 2020 and 2023.
iii. Measure inequalities in latency performance using Gini and Theil indices and Lorenz curves.
iv. Identify good and bad latency regimes using a Markov-switching modelling approach.
v. Compare the forecasting performance of ARIMA, Holt-Winters, Prophet and Random Forest models.

THEORY

The Theory examines previous studies on network latency, ISP performance, temporal variability, inequality measurement, regime-switching models and forecasting approaches. It also identifies gaps in existing research, particularly the limited integration of these methods within the Nigerian ISP context.

Network Latency and Quality of Service

It is well known that one of the most determining aspects of the quality of experience of internet users is network latency. Stojčić et al. (2023) discussed the issue of network latency monitoring ubiquitously and, with minimal overhead, developed an in-kernel method of monitoring network latencies, utilizing eBPF technology. The method was able to run passive and continuous monitoring on an ISP infrastructure device. This approach substantiates the existence of significant variance in latency between different network segments and the potential usefulness of real-time latency monitoring at scale. Sundberg, S. (2024) expanded this effort by integrating an eBPF-based monitoring tool into a wireless ISP network and recording large volumes of latency traces, thereby demonstrating the impact of congestion during peak periods in the last-mile access network.

Network latency is an important component of quality of service because increased delay can affect applications that depend on rapid packet exchange, including voice communication, video conferencing, interactive gaming and real-time data services. For this reason, latency monitoring is important not only for evaluating technical network performance but also for understanding the quality of experience delivered to users.

ISP Performance Measurement

As far as measurement is concerned, geographically distributed observation points such as RIPE Atlas probes have been used to monitor ISP service quality based on latency measurements along different network routes. Such approaches combine measurements including ping and traceroute observations to examine route behaviour and geographical variation in latency. The method provides a useful means of assessing ISP performance from a user-oriented perspective.

Of contextual interest, studies of latency-under-load measurements taken across large networks on a national scale include the FCC Measuring Broadband America programme. These studies reveal significant differences in latency across technology types, including cable, fibre and DSL, and indicate that loaded-network latency measurements are important for approximating realistic user experience. Reed and Perigo (2021) similarly discuss ISP performance measurement within broadband environments, while Komosny (2022) highlights the relevance of latency as an indicator for assessing general internet service performance.

Temporal and Seasonal Behaviour of Latency

Latency performance may vary over time because of changing network loads, routing conditions, demand patterns and infrastructure conditions. Temporal analysis is therefore useful for distinguishing long-term improvements or deterioration from short-term fluctuations. Time-series analysis can also reveal whether recurrent seasonal patterns exist in network performance.

Seasonal-trend decomposition methods are particularly useful for separating observed latency into long-term trend, seasonal variation and irregular components. Such analysis enables researchers to determine whether changes in network performance are persistent or temporary. In the context of ISP performance, this is important because a provider may maintain a relatively low average latency while still experiencing periodic spikes or seasonal deterioration in service quality.

Latency Inequality and Distributional Measures

Surveys also pay increasing attention to the inequality and heterogeneity of latency among different ISPs. The implication highlighted in these studies is the need for statistical tools capable of quantifying disparities in latency distributions rather than relying only on mean performance.

The Gini coefficient and Theil index provide useful measures for assessing inequality in the distribution of latency across service providers. Lorenz curves complement these measures by showing the cumulative distribution of latency and the extent to which performance differs among providers. These techniques allow analysis to move beyond simple average latency and examine whether users experience relatively equal or unequal service conditions across ISPs.

The use of inequality measures is particularly relevant where substantial differences exist between providers. A low overall average latency may conceal significant disparities if a small number of ISPs experience consistently poorer performance. Gini and Theil measures therefore provide an additional dimension for evaluating fairness and consistency in network service quality.

Regime-switching Models in Network Performance

Latency behaviour may also shift between different network states rather than follow a single stable process over time. Markov-switching models provide a method for identifying transitions between latent states, such as relatively good and poor latency regimes. Hamilton (1989) provides a foundational basis for regime-switching analysis, while Lu and Berliner (1999) demonstrate the application of Markov-switching models in time-series contexts.

Within ISP latency analysis, regime-switching approaches can help identify periods of relatively stable service and periods characterised by elevated latency or degraded performance. This adds another layer of analysis beyond averages and linear trends by recognising that network behaviour may change abruptly between distinct operating conditions.

Statistical and Machine-learning Forecasting

Forecasting is increasingly important in network-performance analysis because it can support proactive planning, capacity management and early identification of deteriorating service conditions. Traditional statistical approaches such as ARIMA and Holt-Winters are widely used in

AFRICA HABITAT REVIEW 21(3) 2026

time-series forecasting because they model trend, autoregressive structure and seasonality.

Prophet provides an additional forecasting approach capable of modelling trend and seasonal effects, while machine-learning methods such as Random Forest offer the ability to capture nonlinear relationships and interactions within data. Breiman (2001) established Random Forest as an ensemble-learning method based on multiple decision trees, while Taylor and Letham (2018) developed Prophet for scalable time-series forecasting.

Comparing statistical and machine-learning forecasting methods is important because their performance may differ depending on the structure, variability and complexity of the latency series. Statistical models may perform well where temporal structure is regular, while machine-learning approaches may offer advantages where relationships are nonlinear or highly heterogeneous.

ISP latency studies in Nigeria

Studies of network performance in Nigeria have examined communication systems, quality of service and network reliability from different perspectives. However, relatively limited empirical attention has been given to the combined analysis of latency inequality, temporal behaviour, regime changes and forecasting performance across multiple Nigerian ISPs.

Existing Nigerian studies have often concentrated on specific communication technologies, infrastructure conditions or propagation characteristics rather than on comparative ISP latency performance over an extended period. This creates a need for research that examines several providers within a common analytical framework and evaluates both observed performance disparities and future latency behaviour.

Research Gap

Although previous studies have examined network latency monitoring, ISP performance measurement, temporal behaviour, inequality measures, regime-switching approaches and forecasting methods, these components are often treated separately. Limited research has integrated descriptive statistics, temporal trends, seasonal behaviour, inequality analysis, regime classification and comparative forecasting within a single framework for evaluating ISP latency.

The gap is particularly evident in the Nigerian context, where there is limited comparative evidence across multiple ISPs covering the period from 2020 to 2023. This study therefore addresses the gap by combining descriptive analysis, Gini and Theil inequality measures, Lorenz curves, temporal and seasonal analysis, Markov-switching modelling and comparative forecasting using ARIMA, Holt-Winters, Prophet and Random Forest.

Conceptual Framework

The conceptual framework for this study links the conditions under which Internet Service Providers operate with observed latency performance, inequality in service quality, changes in network states and forecasting outcomes. The framework assumes that ISP and network conditions, together with temporal factors such as changing traffic patterns and seasonal variation, influence the level and variability of latency experienced over time.

Observed latency performance is assessed through descriptive measures and temporal analysis to determine differences among ISPs and identify patterns of improvement, deterioration and fluctuation. Inequality in latency performance is then examined using the Gini coefficient, Theil index and Lorenz curves to establish the extent to which latency is distributed unevenly across providers.

The framework also recognises that network performance may shift between relatively good and poor latency conditions. Markov-switching analysis is therefore used to identify these changing regimes and determine periods associated with comparatively degraded or improved service states.

Finally, the observed latency series provide the basis for evaluating forecasting performance using ARIMA, Holt-Winters, Prophet and Random Forest models. The comparative forecasting results indicate the extent to which different statistical and machine-learning approaches can predict future latency behaviour. Collectively, these relationships support an integrated assessment of ISP performance, latency inequality, regime changes and forecasting capability, with

implications for quality-of-service monitoring and network management.

The conceptual framework presented in **Figure 1** illustrates the relationship between ISP and network conditions, temporal factors, observed latency performance, latency inequality, regime changes and forecasting performance, and how these collectively inform quality-of-service monitoring and network management.

RESEARCH METHODS

This paper carries out multi-stage latency modelling and forecasting in the analysis of internet latency. The work starts with data preparation, followed by descriptive statistics to determine distributions and variability. Inequality indicators such as the Gini and Theil indices measure disparities in performance. Seasonal-trend decomposition and stationarity tests examine temporal effects, while forecasting models ranging from statistical to machine-learning approaches are used to analyse future latency behaviour. The analytical procedure adopted in the study is presented in **Figure 2**.

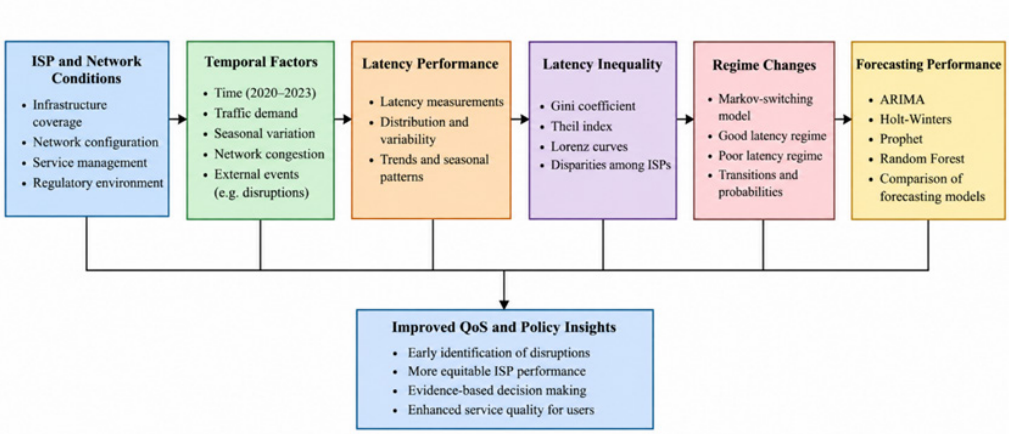


FIGURE 1
Conceptual Framework for the analysis of ISP Latency in Nigeria
Source: Authors' conceptualisation, 2026

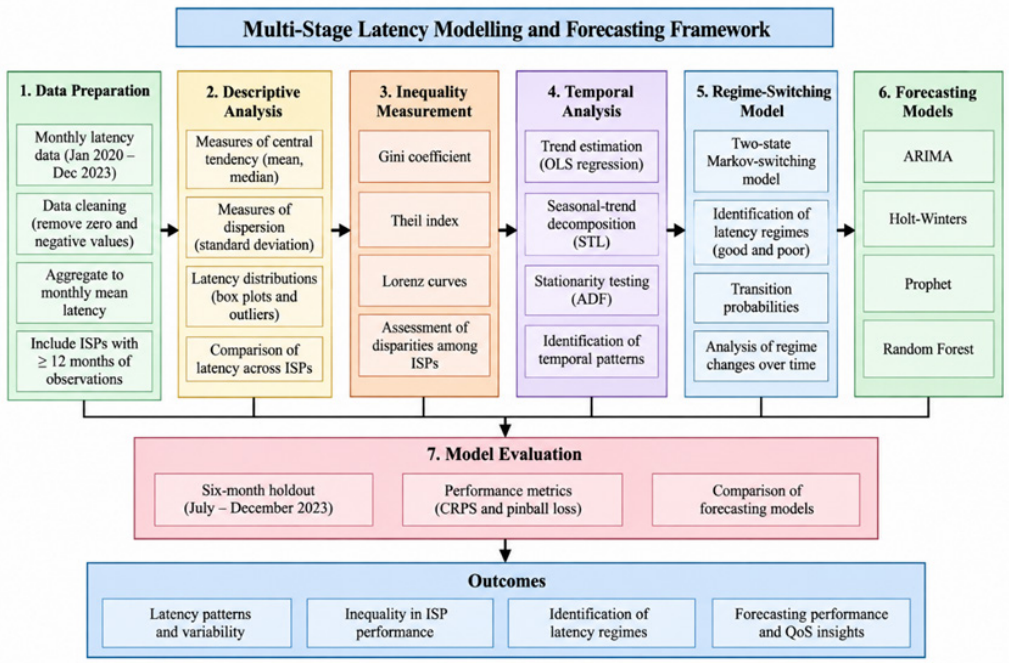


FIGURE 2
Multi-stage latency modelling and forecasting framework
Source: Authors' analytical framework, 2026

AFRICA HABITAT REVIEW 21(3) 2026

Study Area

The study area is Nigeria, located between latitudes 4°N and 14°N and longitudes 3°E and 15°E in West Africa. Geographically, the country lies within the tropics and experiences two distinct seasons: the dry season and the rainy season. The dry season is dominated by a dust-laden air mass from the Sahara Desert, referred to as the Harmattan or Tropical Continental (cT) air mass, whereas the rainy season is largely influenced by a moist air mass originating from the South Atlantic Ocean, known as the southwesterly wind or Tropical Maritime (mT) air mass.

Figure 3 presents the geographical location of Nigeria within the West African region.

Data Preparation

The ISP latency dataset comprised monthly latency measurements for selected Nigerian Internet Service Providers (ISPs) from January 2020 to December 2023, with the analysis based on providers having identifiable and sufficiently available observations during the study period. The data were screened for quality by removing erroneous zero and negative latency values before aggregation into monthly mean latency, while ISPs with fewer than 12 months of valid observations were excluded from time-series forecasting but retained for descriptive analysis.

The dataset covers eight ISPs: Cobrant, Dimension Data, E.Stream, InqDigital, MainOne, Spectranet, VDT and Swift. The study employed descriptive statistics, Gini and Theil inequality indices, Lorenz curves, seasonal-trend decomposition, Augmented Dickey-Fuller testing and a two-state Markov-switching model to examine latency variability, inequality, temporal behaviour and network regimes. Four forecasting approaches—ARIMA, Holt-Winters, Prophet and Random Forest—were subsequently compared using a chronological six-month holdout period from July to December 2023, with Continuous Ranked Probability Score (CRPS) and pinball loss used for performance evaluation. The holdout strategy ensured that future observations were not used during model development and provided a consistent basis for comparing short-to-medium-term forecasting performance.

The statistical and forecasting procedures applied in the study are summarised in **Figure 4**, which presents the descriptive, temporal, inequality,

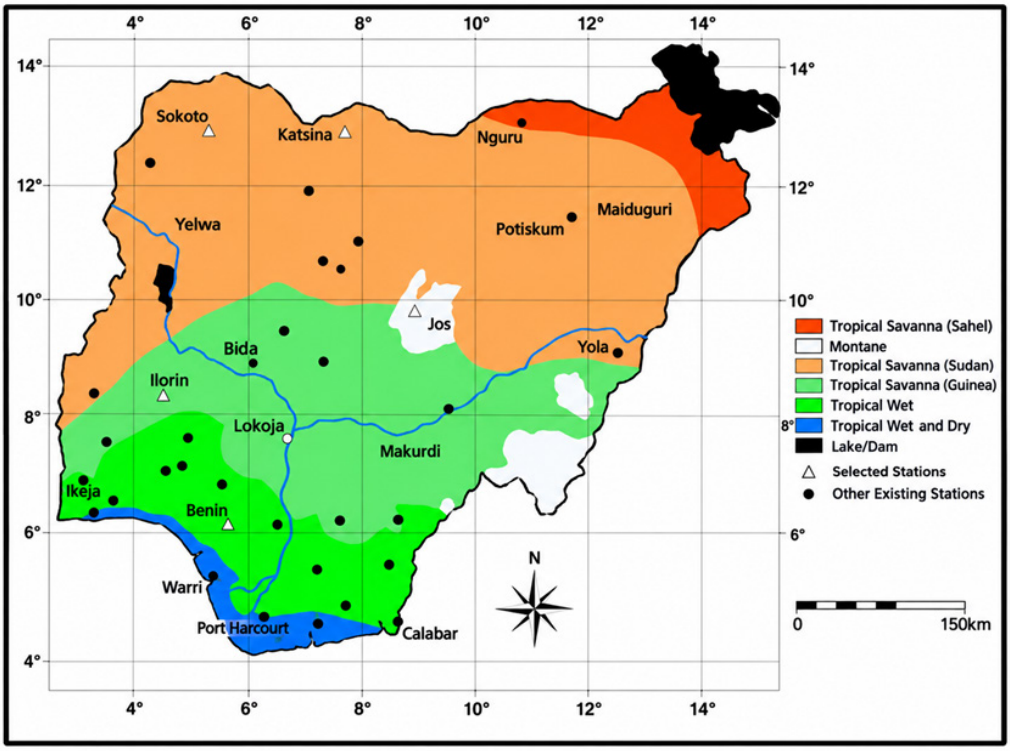


FIGURE 3
Map of Nigeria
Source: Authors' compilation, 2026

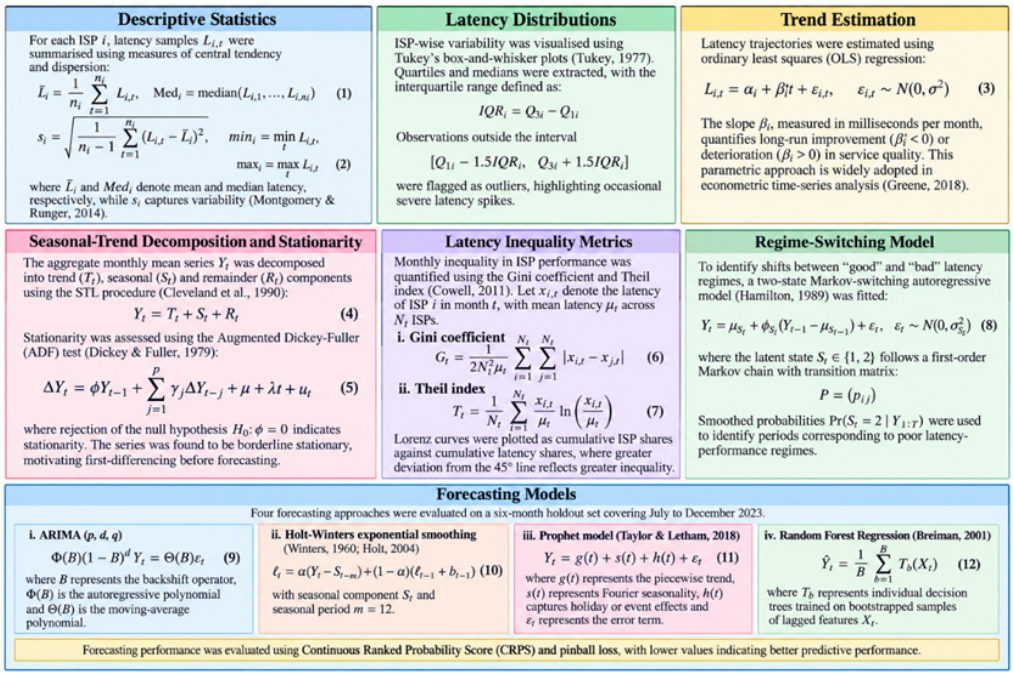


FIGURE 4
Methodological procedures and statistical formulations for ISP latency analysis
Source: Authors' compilation, 2026

regime-switching and forecasting models together with their corresponding formulations.

The procedures presented in **Figure 4** provide the analytical basis for examining latency performance across the selected ISPs. Together, the descriptive, inequality, temporal, regime-switching and forecasting techniques enable the study to assess both observed service behaviour and differences in predictive performance across the models.

RESULTS

The results are presented according to the descriptive, temporal, inequality, regime-switching and forecasting analyses undertaken in the study.

Descriptive Statistics of ISP Latency

Table 1 presents the descriptive statistics of latency performance across the selected Internet Service Providers. The statistics include the number of observations, mean, median, standard deviation, minimum and maximum latency values.

As shown in **Table 2,** Dimension Data recorded the lowest mean latency at 8.04 ms, followed by Cobrant at 11.42 ms and E.Stream at 11.78 ms. InqDigital recorded the highest mean latency at 32.73 ms and the highest maximum latency at 60.82 ms. Dimension Data also recorded the lowest standard deviation at 1.90 ms, indicating comparatively lower variability in its latency observations.

TABLE 1
Descriptive Statistics of Latency Metrics Across Selected ISPs

ISP	Count	Mean	Median	Std. Dev.	Min.	Max.
Cobrant	19	11.42	8.00	8.39	4.00	25.00
Dimension Data	47	8.04	8.30	1.90	2.13	13.28
E.Stream	44	11.78	12.00	6.18	0.18	26.01
InqDigital	46	32.73	30.98	7.27	21.28	60.82
MainOne	48	14.26	13.79	6.14	0.32	28.34

Source: Authors' analysis, 2026

TABLE 2
Monthly latency trends across internet service providers

S/No.	ISP	Slope (ms/month)
1	InqDigital	-0.371
2	Spectranet	-0.316
3	Dimension Data	-0.034
4	MainOne	-0.019
5	VDT Communications	-0.012
6	Swift Networks	-0.011
7	E.Stream	0.159

Source: Authors' analysis, 2026

Latency Distribution Across ISPs

Figure 5 presents the distribution of latency values among the selected ISPs between 2020 and 2023. The box plots show differences in median latency, dispersion and the occurrence of outlying latency observations among providers.

As illustrated in **Figure 5**, Dimension Data recorded relatively low and closely distributed latency observations, while InqDigital and VDT Communications displayed comparatively higher and more variable latency values. Spectranet and Cobrant also exhibited wider latency ranges, while several providers recorded outlying observations representing occasional latency spikes.

Average Monthly Latency Trends

The temporal behaviour of average monthly latency across the selected ISPs is presented in **Figure 6**.

Figure 6 shows fluctuations in average monthly latency throughout the study period. Overall latency tended to decline towards the end of 2023, although a marked latency spike occurred around mid-2022. The available latency observations establish the occurrence of this spike but do not identify its underlying cause. Latency subsequently

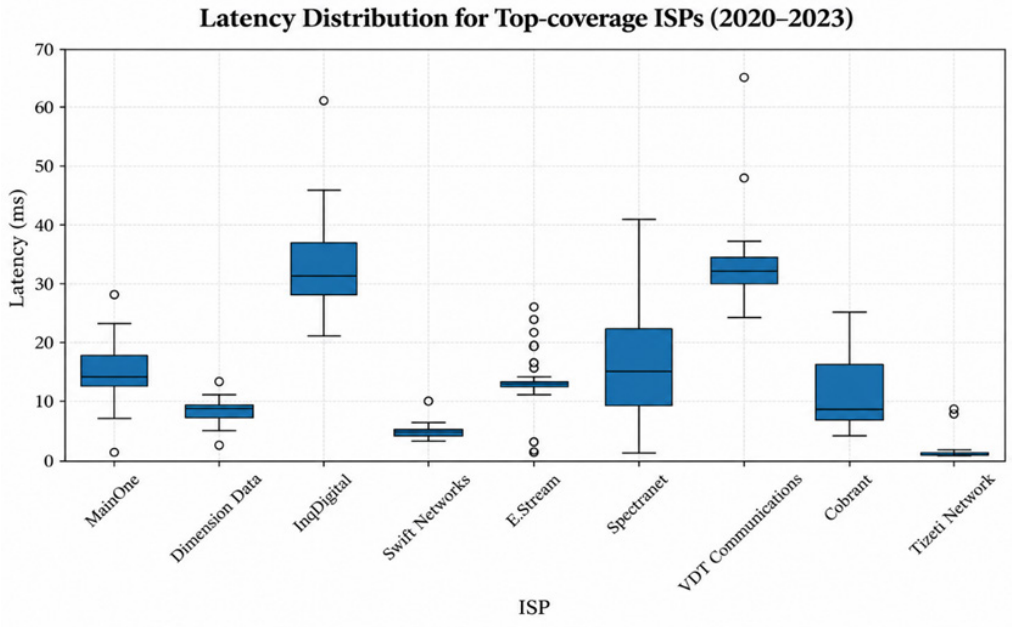


FIGURE 5
Latency distribution among leading ISPs with top data coverage, 2020–2023
Source: Authors' analysis, 2026

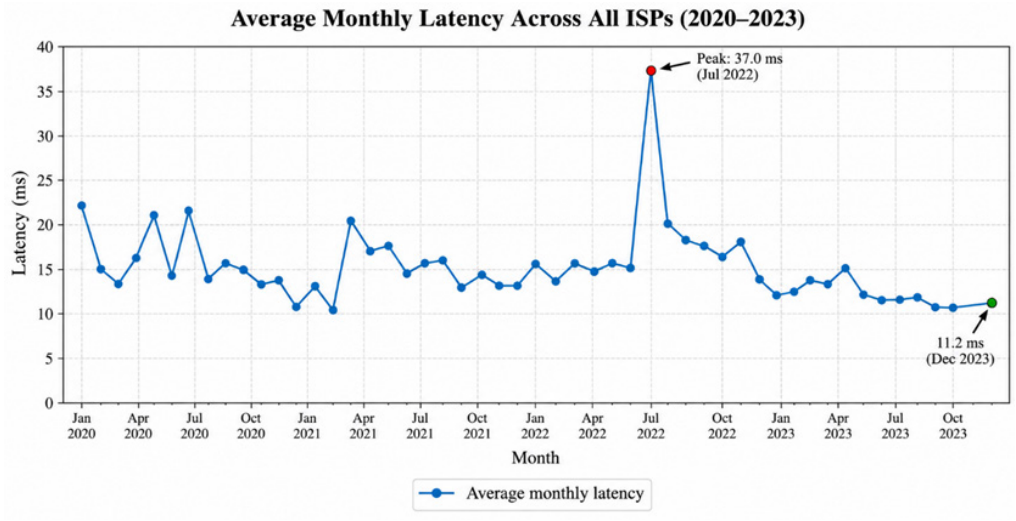


FIGURE 6
Trends in average monthly latency across ISPs, 2020–2023
Source: Authors' analysis, 2026

declined following the mid-2022 increase.

Seasonal-Trend Decomposition

Figure 7 presents the Seasonal-Trend Decomposition using Loess (STL) for MainOne latency observations from January 2020 to August 2023.

As shown in **Figure 7**, the observed latency series fluctuated over the study period, with several notable spikes. The trend component remained relatively stable during the earlier part of the period before declining towards the latter part. The seasonal component fluctuated around zero, indicating recurring variation in the latency series, while the remainder component captured irregular fluctuations not explained by the trend or seasonal components. Outlying residual observations were evident during parts of 2022 and 2023.

ISP Latency Trends

Table 2 presents the estimated monthly latency slopes for seven selected ISPs.

Table 2 shows that InqDigital recorded the largest negative monthly slope at −0.371 ms/month, followed by Spectranet at −0.316 ms/month. Dimension Data, MainOne, VDT Communications and Swift Networks also recorded negative slopes, although these were

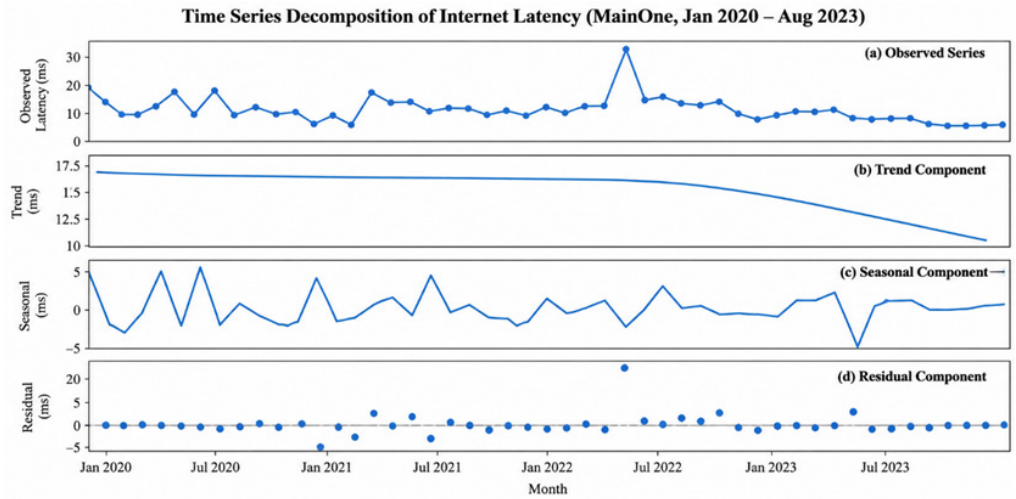


FIGURE 7
Time-series decomposition of internet latency for MainOne, January 2020–August 2023
Source: Authors' analysis, 2026

comparatively small. E.Stream was the only provider recording a positive slope, at 0.159 ms/month. Negative slopes indicate declining latency over time, whereas a positive slope indicates increasing latency.

Figure 8 provides a visual presentation of the latency trends across the selected ISPs during the study period.

As presented in **Figure 8**, InqDigital and Spectranet display overall downward latency trajectories, while Dimension Data and Swift Networks remain comparatively low and stable. E.Stream displays an upward trend, consistent with the positive slope reported in **Table 3**. VDT Communications exhibits greater variation across the observed period.

Latency Inequality

Table 3 presents monthly Gini coefficients, Theil indices and mean latency values used to assess changes in latency inequality across ISPs during the 2020–2023 period.

The values reported in **Table 3** show that both Gini and Theil indices varied across months, indicating changes in the distribution of latency among the selected ISPs over time. For example, the Gini coefficient increased from 0.369 in January 2020 to 0.563 in February 2020 before declining to 0.349 in May 2020. The corresponding Theil values ranged from 0.210 to 0.570 across these reported months.

The distributional changes are further illustrated using Lorenz curves in **Figure 9**.

Figure 9 presents Lorenz curves for January 2020, April 2022 and December 2023. The diagonal line represents perfect equality, while greater departure from this line indicates greater inequality in the

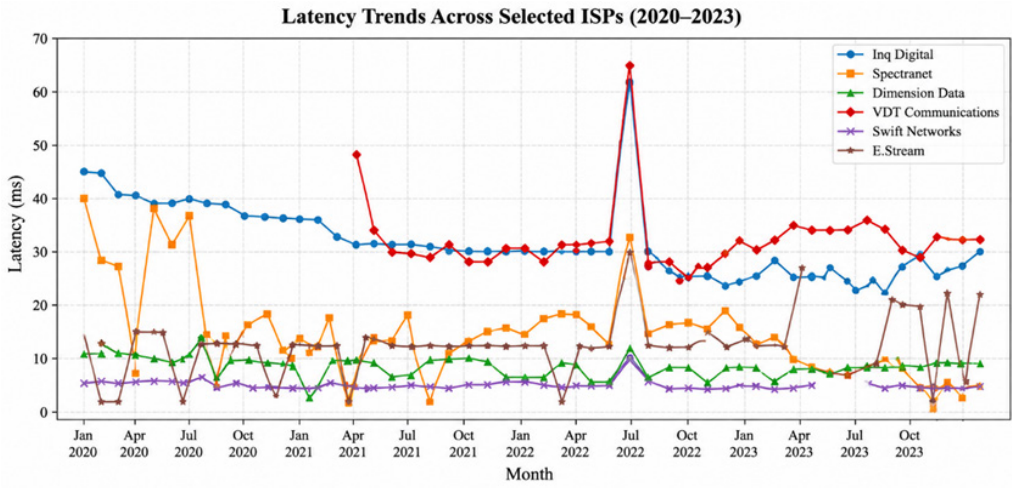


FIGURE 8
Latency trends of selected Nigerian ISPs, 2020–2023
Source: Authors' analysis, 2026

TABLE 3
Monthly measurements of latency and inequality parameters, 2020–2023

Month	Gini	Theil	Mean Latency
2020-01-01	0.369	0.232	22.531
2020-02-01	0.563	0.570	15.186
2020-03-01	0.554	0.553	14.250
2020-04-1	0.384	0.244	16.510
2020-05-01	0.349	0.210	20.780

Source: Authors' analysis , 2026

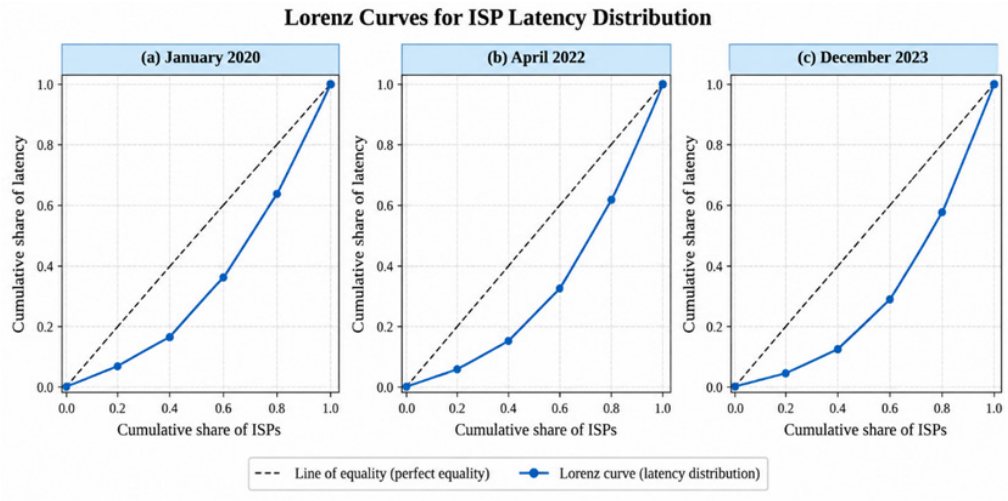


FIGURE 9
Evolution of latency distribution across ISPs, 2020–2023
Source: Authors' analysis, 2026

distribution of latency among ISPs. The curves show differences in latency distribution across the three selected periods and move closer to the equality line by December 2023 compared with January 2020.

Latency Regime Changes

Figure 10 presents the mean latency series alongside the smoothed probability generated by the two-state Markov-switching model.

Figure 10 shows variations in mean latency between 2020 and 2023, including pronounced spikes between late 2021 and mid-2022. The smoothed probability of the poor-latency regime remained relatively low during much of the period but increased around the same period in which mean latency recorded its most pronounced spike. The probabilities subsequently declined as observed latency levels decreased.

Forecasting Performance

Table 4 compares the forecasting performance of Random Forest, Holt-Winters exponential smoothing, ARIMA and Prophet using Continuous Ranked Probability Score and pinball loss.

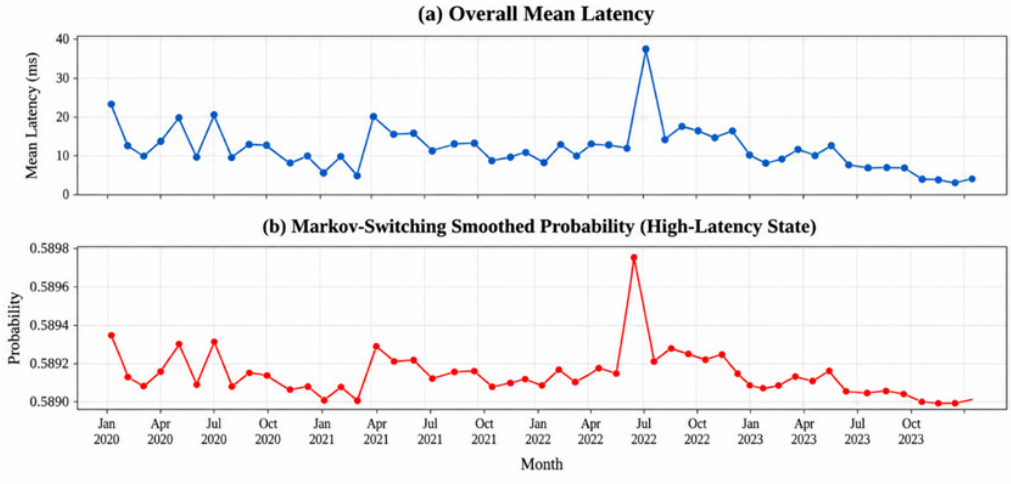


FIGURE 10
Trends in mean latency and network-state probability, 2020–2023
Source: Authors' analysis, 2026

TABLE 4
Model performance comparison using CRPS and pinball loss

S/No.	Model	CRPS	Pinball Loss
1	Random Forest	1.495	1.079
2	HW-ETS	2.367	1.902
3	ARIMA	2.837	2.202
4	Prophet	3.053	1.946

Source: Authors' analysis , 2026

As shown in **Table 4**, Random Forest recorded the lowest CRPS at 1.495 and the lowest pinball loss at 1.079. HW-ETS recorded a CRPS of 2.367 and pinball loss of 1.902, while ARIMA recorded 2.837 and 2.202, respectively. Prophet recorded the highest CRPS at 3.053 and a pinball loss of 1.946. Based on both evaluation measures, Random Forest recorded the lowest forecasting errors among the four models.

Figure 11 presents the six-month forecasting trajectories generated by the four forecasting models.

Figure 11 shows the historical latency series together with forecasts generated for the six-month holdout period from July to December 2023. ARIMA displays comparatively greater forecast fluctuation, Prophet produces a declining trajectory, HW-ETS produces a relatively gradual trajectory, and Random Forest generates a smoother forecast path. The figure therefore shows clear differences in the forecast trajectories produced by the four models.

DISCUSSION

The findings demonstrate clear differences in latency performance among the selected Nigerian Internet Service Providers over the 2020–2023 period. Dimension Data recorded the lowest mean latency, while InqDigital recorded the highest, indicating that users connected through different providers may experience substantially different network-response conditions. This variation supports earlier studies showing that latency differs considerably across network segments, technologies and providers and that average network performance can conceal important differences in user experience (Stojčić et al., 2023; Komosny, 2022). The comparatively low standard deviation recorded by Dimension Data further indicates greater consistency in its latency observations, whereas the wider distributions recorded by some providers reveal greater variability in service performance.

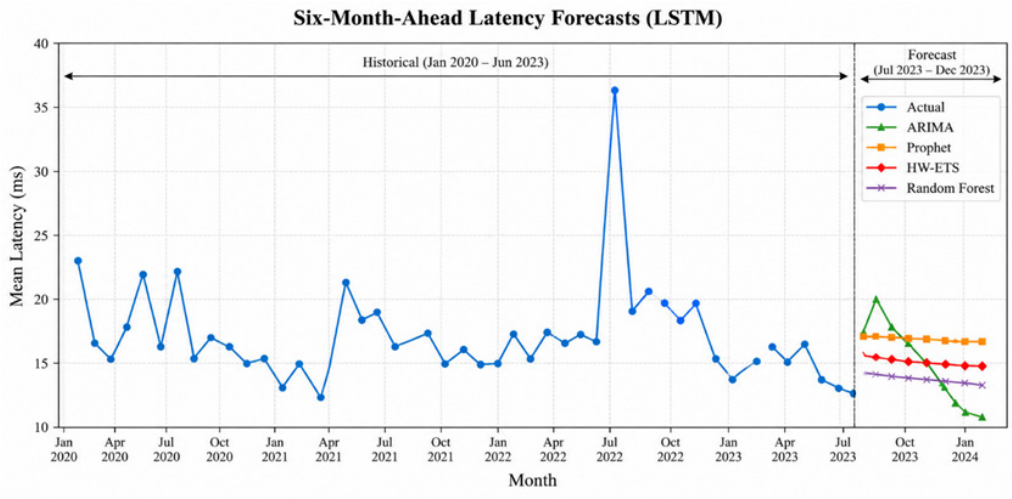


FIGURE 11
Six-Month-ahead latency forecasts by different models
Source: Authors' analysis, 2026

Temporal Trends and Seasonal Behaviour
The temporal analysis revealed an overall decline in average latency towards the end of the study period, although substantial fluctuations occurred between 2020 and 2023. A pronounced spike was observed around mid-2022, followed by lower latency levels thereafter. The available data establish the occurrence of this latency increase but do not independently identify its underlying cause. The observed temporal variation is consistent with previous studies demonstrating that latency changes over time and can be affected by variations in network load, routing conditions and demand patterns (Sundberg, S. (2024); Komosny, 2022).

The seasonal-trend decomposition further showed that the latency series contained distinguishable trend, seasonal and irregular components. The trend component declined during the latter part of the period, while the seasonal component fluctuated around zero and the residual series contained occasional large deviations. These findings reinforce the usefulness of time-series decomposition in distinguishing persistent changes in network performance from temporary or recurring fluctuations. The results therefore suggest that ISP performance should not be evaluated solely from overall averages because temporal patterns may reveal periods of comparatively better or poorer service that would otherwise remain concealed.

Differences in ISP Latency Trends
The estimated monthly slopes further revealed differences in the direction and magnitude of latency change among providers. InqDigital and Spectranet recorded the largest negative slopes, while Dimension Data, MainOne, VDT Communications and Swift Networks recorded smaller negative values. E.Stream recorded a positive slope, indicating increasing latency over the period examined.

These results show that providers with high latency levels may nevertheless record improving temporal trends, while providers with relatively low latency may exhibit limited change over time. This distinction is important because current performance and direction of change represent different dimensions of service quality. The findings are consistent with studies emphasising the need for continuous latency monitoring rather than relying on isolated measurements of average performance (Stojčić et al., 2023; Sundberg, S. (2024). Continuous monitoring allows both the existing level of latency and the direction in which performance is changing to be assessed.

Inequality in Latency Performance
The Gini coefficient, Theil index and Lorenz curves revealed that latency was not equally distributed across the selected ISPs. Monthly inequality levels varied over time, indicating that disparities in service performance were not constant throughout the study period. The movement of the Lorenz curves closer to the line of equality by December 2023 compared with January 2020 indicates a more balanced distribution of latency among providers during the later period.

The use of distributional measures extends conventional QoS assessment beyond the comparison of average latency. While mean latency provides information about general network performance, Gini and Theil indices show how that performance is distributed among providers. This is particularly important in environments where users depend on different ISPs and may therefore experience markedly different service conditions. The findings support the argument that inequality measures can complement traditional QoS indicators by identifying disparities that are not evident from aggregate averages alone (Cowell, 2011).

From a regulatory perspective, these results indicate that an improvement in national or aggregate latency does not necessarily mean that all users are benefiting equally. Monitoring frameworks should therefore consider both average performance and the distribution of performance across providers. Such an approach would make it easier to identify persistent service disparities and providers whose performance differs substantially from the broader market.

Regime Changes in Latency Performance
The Markov-switching analysis identified variation between relatively favourable and poor latency-performance states. The smoothed probability associated with the poor-latency regime increased during the period in which mean latency recorded its most pronounced spike. This correspondence suggests that the model was able to distinguish changes in the state of network performance

AFRICA HABITAT REVIEW 21(3) 2026

rather than relying only on gradual linear trends.

This finding is consistent with Hamilton's (1989) regime-switching approach, which recognises that time-series behaviour may shift between distinct underlying states. Lu and Berliner (1999) similarly demonstrate the usefulness of Markov-switching models for analysing changes between different states in time-series data. Applied to ISP latency, the approach provides an additional mechanism for identifying periods when observed network conditions depart from their more typical state.

The regime results should, however, be interpreted as statistical indications of different latency states rather than as direct evidence of particular technical failures, congestion events or infrastructure disruptions. Identifying the precise causes of individual regime changes would require additional operational or network-event data beyond the latency observations used in this study.

Forecasting Performance

The comparison of forecasting models showed that Random Forest recorded the lowest CRPS and pinball loss, followed by Holt-Winters exponential smoothing, while ARIMA and Prophet recorded higher forecasting errors. Random Forest therefore provided the strongest predictive performance among the four models examined.

The superior performance of Random Forest indicates that machine-learning approaches may offer advantages when latency behaviour contains nonlinear relationships and irregular fluctuations that are difficult for conventional statistical models to capture. Breiman (2001) notes that Random Forest combines multiple decision trees to improve predictive accuracy and robustness. In contrast, ARIMA and Holt-Winters depend more directly on identifiable temporal structures such as autoregression, trend and seasonality, while Prophet is designed to model trend and seasonal components through an additive structure (Taylor & Letham, 2018).

The finding does not imply that statistical forecasting approaches are unsuitable for latency modelling. Rather, the results indicate that model performance depends on the characteristics of the dataset being analysed. The forecast trajectories also differed considerably across models, reinforcing the importance of evaluating competing models using common performance measures rather than selecting a forecasting method solely on theoretical preference.

Implications for ISP Management and Regulation in Nigeria

Taken together, the findings indicate that latency management in Nigeria requires attention to average performance, variability, inequality, changing network states and future performance simultaneously. Relying on a single QoS indicator may provide an incomplete picture of service conditions.

For ISPs, continuous monitoring of latency trends and regime probabilities could support earlier identification of periods of deteriorating service performance. Inequality measures can also help determine whether network improvements are occurring consistently across providers rather than being concentrated among a limited number of operators.

For regulators, the findings support the value of standardised and comparable latency reporting across ISPs. Such reporting could incorporate measures of average latency, variability and distributional inequality to provide a broader assessment of service quality. Forecasting tools may further assist in identifying emerging performance patterns before they become persistent service-quality problems.

Overall, the study demonstrates that combining descriptive analysis, temporal modelling, inequality measurement, regime-switching analysis and forecasting provides a broader assessment of ISP latency than reliance on average latency alone. The integrated approach therefore contributes to understanding both differences in current ISP performance and changes in service conditions over time.

CONCLUSION

The study shows that Nigerian ISPs have substantial differences in latency, temporal behaviour and service inequality. Overall latency generally declined between 2020 and 2023, although marked latency spikes and persistent disparities were observed, particularly around mid-2022. Dimension Data recorded the lowest mean latency of 8.04 ms, while InqDigital recorded the highest

mean latency of 32.73 ms. Inequality measures and Markov-switching analysis identified variations in the distribution of latency and periods associated with comparatively poor service states. Random Forest provided the most precise forecasts, achieving a CRPS of 1.495 and pinball loss of 1.079, indicating its effectiveness for ISP latency forecasting and QoS management.

The study was limited by the available data coverage, the number of ISPs represented and the use of monthly observational latency records. The analysis also relied on latency measurements without corresponding operational records that could independently explain the causes of individual latency spikes or regime changes. These limitations should be considered when interpreting the findings and their wider application.

RECOMMENDATIONS

i. *Strengthen continuous latency monitoring across ISPs.*
Internet Service Providers should implement continuous latency monitoring systems that combine conventional latency indicators with Gini and Theil inequality measures. This would enable providers to identify not only changes in average performance but also widening disparities and emerging periods of poor service performance across networks.

ii. *Integrate regime-switching analysis into QoS monitoring.*
ISPs should incorporate Markov-switching regime classification into network-performance monitoring to identify transitions between relatively good and poor latency conditions. Such monitoring can provide early indications of unusual performance patterns and support timely technical assessment before poor service conditions persist.

iii. *Adopt predictive forecasting tools for network management.*
Random Forest forecasting should be integrated into QoS management systems to support proactive capacity planning and infrastructure maintenance. Its comparatively lower forecasting errors in this study indicate that it can complement conventional statistical forecasting approaches when monitoring changing latency patterns.

iv. *Establish standardised latency reporting requirements.*
Regulators should establish standardised reporting requirements that allow transparent comparison of ISP latency performance. Such reporting should include mean latency, variability, inequality measures and temporal performance indicators so that differences among providers can be assessed consistently over time.

v. *Target infrastructure investment towards poorly performing networks and areas.*
Investment in network infrastructure should prioritise locations and service environments where latency remains comparatively high or unstable. Periodic data-driven assessments should be used to identify priority areas and guide interventions aimed at improving reliability and reducing performance disparities.

vi. *Conduct periodic comparative assessments of ISP performance.*
Regulators and service providers should undertake regular comparative assessments using consistent datasets and analytical methods. This would make it possible to track whether service quality is improving, deteriorating or becoming more equitable across different providers.

vii. *Expand future research using more detailed operational data.*
Future studies should incorporate higher-frequency latency measurements, a broader range of ISPs and operational network records. This would allow researchers to examine the causes of latency spikes and regime changes more directly and strengthen the reliability of forecasting and policy conclusions.

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