Data-Driven Monitoring Framework for Rural Digital Infrastructure: Evidence from Internet Speed Trends and Forecast-Based Quality Control in the Samarkand Region

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Abstract: Digital infrastructure is a crucial factor for inclusive growth, and rural digital service quality, especially in developing economies, is still behind that of cities. Therefore, continuous monitoring and short-term forecasting of service quality is important for effective management of digital infrastructure. This study presents a data-based approach for monitoring rural internet service quality in Uzbekistan, with average speed measured in Mbps being considered a fundamental service quality parameter. The study focuses on rural areas in the Samarkand region, with internet speeds measured monthly over a sample period from March 2022 to December 2025, totalling 46 observations. The objectives of this study include: (i) establishing the existence of a significant trend in rural internet speeds, (ii) establishing whether there is an annual seasonal effect, and (iii) establishing whether short-run forecasts are suitable for operations. The study employed a deterministic linear trend equation, a unit root test with seasonal differencing, and a SARIMA model, with Stata being employed for estimation purposes. The results indicate that there is a strong, significant trend in rural internet speeds, with an average increase of about 0.48 Mbps per month, with $\beta = 0.484$, $p < 0.01$. The study also indicates that there is no complete removal of non-stationarity by employing a seasonal difference, with a p-value of 0.4775, indicating that there is a long-term development trend. Using the results obtained, a proposed automated monitoring logic is presented, with trend and forecast deviations being considered signals for service quality. This study provides a useful approach towards developing monitoring solutions that will be useful for monitoring rural IT service quality, especially in developing economies.

1 INTRODUCTION

Digital infrastructure is an essential component in modern economic growth and social integration. A substantial amount of empirical evidence, including systematic literature reviews [1], broadband infrastructure and ICT connectivity contribute significantly to regional growth, expanding the market reach of enterprises, and providing essential public services that are necessary for economic growth. However, despite the overall growth of broadband infrastructure, the phenomenon of the digital divide between urban and rural regions persists [2] This general characterization of the urban-rural divide reflects the broader digital-divide literature rather than speed-specific data drawn directly from [2]; the quantitative internet-speed evidence specific to Uzbekistan and the Samarkand region presented in this study is developed. Rural regions have been affected to a greater extent in terms of connectivity challenges, highlighting infrastructural gaps, especially in developing countries like Uzbekistan [2]. Dispersed population density, where connectivity needs to reach over long distances in low-density areas, is a high-cost, low economies of scale market with low ROI for telcos [1]. In addition, it is found that deploying network infrastructure is 80% higher in cost in rural regions compared to urban regions [3] This figure is drawn from a study of the United States broadband market and has not been independently verified for the Uzbek context; it is cited here as an indicative order-of-magnitude reference for the general economics of rural network deployment rather than as a measured value specific to Uzbekistan or the Samarkand region.. This is a limitation to the growth of the rural digital economy, where the cost of accessing high-speed internet is very expensive, as well as the low rate of [4]. The impact of this phenomenon is high, including essential sectors like education, healthcare, environmental conservation, and social inclusion, thus limiting societal growth [4].

This gap is compounded by the unaffordability of high-speed internet in rural areas, as well as a lack of digital literacy [1], [4]. The digital divide is not only about a lack of connectivity, but also about variations in the level of infrastructure, usage potential, and availability of supporting resources [1], [5]. The literature has also emphasized that digital infrastructure, although a prerequisite for economic development, is only a necessary but not a sufficient condition for development [1]. This is because, while infrastructure provides development potential, for maximum utilization, human capital factors are also needed. This is because, without these, development outcomes are limited, considering that infrastructure costs may be as much as 80% higher in rural areas than in urban areas [1], [3]. It is, therefore, crucial to address the gaps in digital infrastructure as well as human capital for achieving digital economic development, especially in areas such as rural Uzbekistan, where there is a huge urban-rural speed divide [2]. The goal of this paper is to fill an important gap in the existing research by developing a data-based framework to track digital infrastructure, including internet speeds and forecast quality control in Samarkand Region. The persistent underdevelopment of rural areas in digital infrastructure can cause digital exclusion [6]-[10]. The disparities will also be deepened by the increasing recognition that high-speed internet connectivity is a fundamental driver of economic and educational inclusion, with limited connectivity resulting in systematic disadvantages for rural populations [11]. The maintenance and development of rural digital infrastructure are important policy and tech issues. In practical terms, a digital backbone involves not just checking, but monitoring, service quality. Monitoring-based approaches focus on QoS, i.e., “speed, stability, and predictability,” and its role in QoS systems. The digital divide is said to vary in different aspects, including infrastructure and users’ skills. The developing world, such as Uzbekistan, can benefit from a strong internet infrastructure to support precision agriculture, education, telemedicine, and more involvement of SMEs in rural areas. Rural areas in Europe have already demonstrated higher turnover and value added for enterprises. Digital transformation is a key focus for Uzbekistan to build infrastructure and bridge the gap between urban and rural areas. Samarkand is an example of this combination of urban and rural areas along with the influence of internet penetration on the agriculture-based rural areas of Uzbekistan.

Past research on the digital economy in Uzbekistan has centered on descriptive evaluations of digitalization processes and developments in e-governance services at the regional level [12]. Although previous research has highlighted regional disparities in the adoption of digital services and infrastructure, few have attempted to investigate the dynamic performance of the internet in rural areas. Most of the previous research has used static methods, which cannot effectively show changes over time, considering the urban and rural disparities. Dynamic internet speed measurement in Mbps can effectively show changes over time, considering infrastructure and speed differences. Previous studies have indicated that environmental factors play a role in influencing the performance of broadband infrastructure, which may include seasonal effects due to topography. This paper helps fill the gap by examining the performance of internet infrastructure in rural areas, including temporal aspects. It employs a rigorous econometric approach to analyze monthly internet speeds (in Mbps) in rural districts in the Samarkand region of Uzbekistan from March 2022 to December 2025 [2]. This study goes beyond static speed data to dynamic measures of network efficiency, utilization, and user experience [1], [2]. The objectives of this research are as follows: to test for significant positive long-run trends in internet speeds in rural districts of Uzbekistan’s Samarkand Region; to seriously investigate annual seasonal fluctuations in internet speeds and their determinants, as suggested by the meteorological impacts on internet speeds [12]-[15] and to examine the accuracy of short-run forecasts, including their reliability, in line with research evidence on their use in quality control [16]-[18]. By focusing on econometric time series analysis within a data-driven monitoring framework, this study aims to contribute to the IT literature with practical illustrations of leveraging time series to facilitate automated monitoring, network degradation detection, and design of a performance optimization management system for rural areas toward building digital economies within resource-scarce environments of less developed countries [4], [18], [19]. This is because, much like water or electricity, broadband performance in rural areas is a basic utility that is essential for development, education, and social welfare [11].

The gap between internet access and speed between rural and urban areas of Uzbekistan is an example of digital divide, with rural areas having lower internet speeds than cities [2]. The gap often prevents the actual potential of ecotourism and hospitality industries in the inner regions, where internet infrastructure gaps hinder economic and social development [20].

2 METHODOLOGY

2.1 Data and Research Design

The research will employ a quantitative research design, utilizing a quantitative time-series approach to analyze the temporal characteristics of internet speed in rural regions within the Samarkand region of Uzbekistan. The empirical data will consist of 46 observations, spanning from March 2022 to December 2025, with internet speed measured in megabits per second [21]. Data will be collected from internet performance monitoring systems, which log the throughput of the internet at regular intervals. This ensures that the data collected will have a uniform structure. Specifically, monthly average download-speed observations for the study area were extracted from the Giga Global Maps platform [21] (a UNICEF/ITU-supported connectivity-mapping initiative that aggregates crowdsourced and network-provider speed-test records at the district level), covering March 2022 through December 2025 (n=46 monthly observations); these raw platform extracts were then compiled and analyzed in Stata by the authors [22]. The reported trend coefficient (beta=0.484 Mbps/month) should therefore be interpreted as the average monthly change in this aggregated, crowdsourced speed-test metric over the observed window, rather than as a directly audited network-operator measurement; potential sources of measurement variability (e.g., changes in the underlying pool of contributing devices/tests over time) are acknowledged as a limitation in Section 4.4. The quality of the internet infrastructure of the region will be indicated by the speed of the internet. Collecting the data monthly will account for the increase in the speed of the internet over time, which could be due to various reasons such as usage, climate, etc. All the statistics will be calculated using the Stata programming language. The time dimension will be specified in the data.

2.2 Hypothesis H1: Long-Term Trend Analysis

To evaluate whether average monthly internet speed improves over time, the study estimates a deterministic linear time-trend model via Ordinary Least Squares (OLS), specified as:

$$Speed_t = \beta_0 + \beta_1 \cdot Time_t + \varepsilon_t , \quad (1)$$

where:

- $Speed_t$ denotes the observed average internet speed (Mbps) in month t;
- $Time_t$ is a monthly time index capturing the progression of time (e.g., 1, 2, …, 46);
- β_0 is the intercept term (baseline level when $Time_t = 0$);
- β_1 measures the direction and magnitude of the long-run trend; a positive and statistically significant β_1 indicates sustained improvements in internet speed over time;
- ε_t is the stochastic disturbance term capturing unobserved factors affecting internet speed in month t.

A positive $\beta 1$ value implies that internet speed is increasing over time, providing an interpretable test for whether digital infrastructure is improving over time. The hypothesis is subject to standard tests of significance, where the sign and p-value of the time coefficient are examined.

2.3 Hypothesis H2: Seasonality and Stationarity

Given the visual and descriptive evidence of recurring within-year fluctuations, the study evaluates the presence of annual seasonality by applying a 12-month seasonal differencing operator to the monthly internet speed series. The seasonal transformation is defined as:

$$\Delta_{12} Speed_t = Speed_t - Speed_{t-12} , \quad (2)$$

where:

- $\Delta_{12}Speed_t$ denotes the seasonally differenced value in month t;
- $Speed_t$ is the observed average internet speed (Mbps) in the current month t;
- $Speed_{t-12}$ represents the observed average internet speed (Mbps) in the same calendar month of the previous year.

This transformation removes deterministic seasonal patterns with a 12-month periodicity and facilitates subsequent stationarity testing and seasonal time-series modeling.

In order to formally test the stationarity, the Augmented Dickey-Fuller (ADF) test should be performed for the original series as well as the seasonally differenced series. The Augmented Dickey-Fuller approach is used for the detection of the presence of unit roots in the time series, thereby checking for the presence of stochastic trends after the elimination of seasonal patterns. The hypothesis is confirmed if the time series is found to be non-stationary at the level while the seasonally differenced time series is found to be stationary.

2.4 Hypothesis H3: Forecasting and Model Stability

To assess the predictability and stability of future internet speed behavior, the study estimates a parsimonious Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The selected specification is designed to achieve an appropriate balance between explanatory power and model simplicity and is given by:

$$\mathrm{SARIMA}(0,1,1)(0,1,1)_{12}. \quad (3)$$

In particular, the model employs the following components:

- Non-seasonal differencing d=1 to account for stochastic trends in internet speed;
- Seasonal differencing D=1 to account for seasonal variations;
- Non-seasonal moving-average component q=1 to account for short-run shocks;
- Seasonal moving-average component Q=1.

This parsimonious SARIMA model employs trend removal, seasonal adjustment, and moving averages to offer a versatile yet stable approach to short-term forecasts and evaluating rural digital infrastructure performance. For purposes of evaluating the predictive power of the model, it was also compared to another model: the Naïve Seasonal Model. The error value for the Naïve Seasonal Model was significantly high (SD = 10.08) compared to SARIMA, validating its accuracy in rural internet speeds' trend detection. For evaluating the SARIMA model's performance, common information criteria are applied alongside residual tests for model adequacy. A one-year-ahead forecast will also be conducted to assess forecast stability and confidence interval widths for evaluating internet speeds' predictability using rural digital infrastructure.

2.5 Analytical Logic and Contribution

The methodological framework follows a logical sequence of trends (H1), accounting for seasonality/stationarity (H2), and then forecasting/stability (H3). This holistic approach to research methodology ensures that empirical research is statistically sound and relevant. This blend of classical econometrics and modern forecasting techniques strikes the right balance between being accessible to student-level conference work yet academically sound.

2.6 System-Level Application Logic

In addition, the econometric model provided here also functions as the "brain" of the automated rural digital infrastructure monitoring system. The OLS trend represents the standard performance, while the SARIMA forecast represents the expected range of operation. Any difference between the actual speeds and the forecast speeds will serve as indicators of potential problems. In other words, the econometric model can be translated into a computer-readable format that can be used as input to the rural digital infrastructure management decision support systems.

2.7 QoS Monitoring Logic Pseudocode

Algorithm: InternetSpeedQualityControl.

Input: ActualSpeed (V_{act}), ForecastedSpeed (V_{for}), Threshold (T = 0.20).

Output: SystemAlert

1) Calculate deviation :

$$D = (V_{for} - V_{act}) / V_{for}.$$

2) If D > T then:
3) Generate alert: "Performance degradation detected";
4) Log issue: Record time and magnitude of deviation;
5) Else:
6) Status: "Service quality normal".

The threshold T = 0.20 is a relative (fractional) threshold, as defined by the deviation formula D = (V_for - V_act) / V_for above, meaning an alert is triggered when actual speed falls more than 20% below the SARIMA-forecasted speed for that month. This value was chosen as an illustrative, conservative starting threshold intended to filter out normal month-to-month measurement noise (which, based on the residual variability of the fitted SARIMA model in Table 3, is typically well under 20%) while still flagging materially significant degradations; it is a tunable operational parameter that network administrators would calibrate against local tolerance for false positives versus missed degradation events, rather than a value derived from a formal optimization procedure in this study. As a worked example: if the SARIMA model forecasts V_for = 25 Mbps for a given month and the actual measured speed is V_act = 18 Mbps, then D = (25-18)/25 = 0.28, which exceeds T = 0.20, and the algorithm would generate a "Performance degradation detected" alert; if instead V_act = 21 Mbps, D = 0.16 < T, and the status would read "Service quality normal."

3 RESULTS

As seen from the regression, there is a strong positive relationship between time (t) and internet speeds (speed_mbps). Time, therefore, has a positive coefficient that is significant, suggesting that the speed increases by 0.48 units with each unit of time.

The intercept is negative; this is not inherently "expected" in a general sense, but follows directly from extrapolating the fitted linear trend back to t=0 (the start of the observation window in March 2022): given the observed positive slope, a negative intercept simply reflects that the regression line, when extended backward, crosses zero before the start of the sample, which is a common and unremarkable feature of linear trend fits over a window that does not include t=0 in a meaningful physical sense, and carries no substantive interpretation about internet speeds at any real historical time point.

The model is able to explain about 44.7% of the variance of the speeds ($R^2 = 0.447$) and is significant overall ($F = 35.61$, $p < 0.001$) with 46 observations.

The test statistic, ($Z(t) = -1.611$), is greater than all critical values at 1%, 5%, and 10% significance levels. Moreover, the MacKinnon p-value of 0.4775 is greater than standard values. Therefore, the null hypothesis cannot be rejected. The results indicate that the 12-month differenced internet speed data is non-stationary. More precisely, since seasonal differencing (a 12-month difference) has already been applied at this stage, non-stationarity of the resulting series indicates the presence of a remaining stochastic trend in the seasonally differenced data, rather than unremoved seasonality per se; seasonality itself, as a repeating within-year pattern, is addressed separately by the seasonal differencing operation, while this stochastic-trend finding motivates the additional (non-seasonal) differencing applied in the SARIMA specification in Table 3 below.

Table 1: OLS trend regression results [22].

Var.	Coef.	St. Err.	t	p	[95% CI]
Time (t)	0.484***	0.081	5.97	0.000	[0.321; 0.647]
Cons.	-336.408***	60.225	-5.59	0.000	[-457.72; -215.033]
R-squared: 0.447			F(1, 44): 35.61		
Observations: 46			Prob > F: 0.000		
AIC: 315.41			BIC: 319.07		
Mean dep. var: 22.921					
*** p<0.01, ** p<0.05, * p<0.1					

Table 2: Augmented Dickey-Fuller test for seasonality [22].

Variable		d12_speed	
Number of Observations		21	
Number of Lags		12	
Null Hypothesis (H_0)		Random walk without drift (d = 0)	
Test Statistic Z(t)	1% Critical Value	5% Critical Value	10% Critical Value
-1.611	-3.750	-3.000	-2.630
MacKinnon Approx. p-value		0.4775	

Table 3: SARIMA model estimation.

Var.	Coef.	St. Err.	z	P>|z|	[95% CI]
AR (L1)	-0.028	0.184	-0.15	0.879	[-0.389; 0.333]
MA (L1)	-0.438	0.269	-1.63	0.104	[-0.966; 0.090]
Cons.	-0.452	0.698	-0.65	0.517	[-1.821; 0.917]
Sig.	4.864***	0.763	6.38	0.000	[3.369; 6.359]
Number of obs = 33			Mean dep. var = -0.191		
Chi-square = 2.686			SD dep. var = 5.519		
*** p<0.01,**p<0.05,* p<0.1					

The seasonally differenced series (DS12.speed_mbps) does not show any statistically significant AR patterns. The coefficients are small and not significant at all ($p > 0.10$). There is one constant term that is significant at $p < 0.01$, which does not impact the results. The result is that, after 12-month differencing, there are no autoregressive patterns in internet speeds, which means there are no short-run patterns.

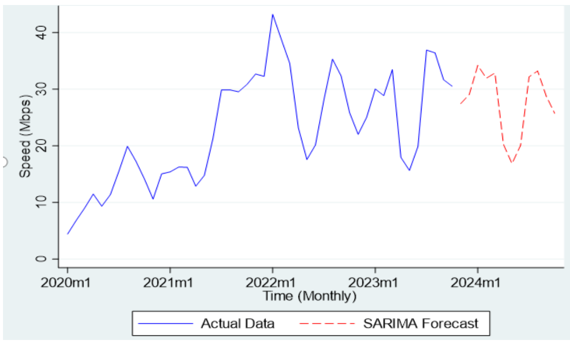

Figure 1: Internet speed: final SARIMA forecast [22].

The Figure 1. shows the time series trend of the monthly internet speed in Mbps from 2020 to 2024. The data shows fluctuations with strong seasonal fluctuations. The forecast results obtained using the SARIMA model are reliable in predicting the continuation of the seasonal fluctuations in the future.

From a system monitoring perspective, it can be noted that the lack of strong autoregressive dynamics in the short run suggests that large deviations from expected internet speed values may be due to outside influences rather than internal network cycles.

4 DISCUSSION

This section discusses the results of the analysis in the context of the three research hypotheses developed in this research, placing the econometric results in a broader context of the development of rural digital infrastructure in the Samarkand region of Uzbekistan.

4.1 Hypothesis H1: Long Run Evolution of Internet Speed

This hypothesis holds that internet speed in rural Samarkand, Uzbekistan, exhibits a statistically significant trend of increase. This is validated by the OLS trend model, as represented in Table 1, whereby the time coefficient is positive and very significant ($\beta = 0.484$, $p < 0.01$), implying that internet speed is rising by about 0.48 Mbps on average each month. This is a systematic increase, rather than a random change, and is quite significant. The model accounts for about 45% of variation in internet speed, and the high F-statistic also indicates a very significant trend.

4.2 Hypothesis H2: Seasonal Effects and Stationarity

Moreover, H2 also hypothesizes that there are yearly variations in internet speed, and that by applying 12 months of seasonal differencing, the series will be made stationary. However, as indicated by the Augmented Dickey-Fuller Test (Table 2), the series is non-stationary even after differencing (p-value = 0.4775). This indicates that, to a certain extent, hypothesis H2 is true, as there are yearly variations, but seasonal variations are not entirely a determinant of this series, as indicated by the fact that long-term determinants, such as ongoing upgrades, technological advancements, and rising demand, are more prominent.

This also indicates a methodological aspect, whereby, when working with infrastructure-related series, more than seasonal differencing is necessary, as indicated by strong developmental trends.

4.3 Hypothesis H3: Forecast Stability and Model Performance

Hypothesis H3 tests whether a parsimonious SARIMA model provides a stable short-term forecast for internet speed. As indicated in Table 3, the short-run autoregressive parameters for seasonally differenced speed are small and statistically insignificant, and lag parameters are small and statistically insignificant too (specifically, AR(L1) = -0.028, $p = 0.879$, and MA(L1) = -0.438, $p = 0.104$). This indicates that, after differencing for trend and seasonality, the remaining short-run fluctuations in internet speed are not well explained by the series' own recent past values (i.e., little evidence of autoregressive or moving-average memory), which is consistent with, though does not on its own prove, month-to-month changes being driven more by external, non-recurring factors (e.g., infrastructure upgrades, provider-specific changes) than by predictable internal cycles. One intercept is statistically significant, but this does not change our understanding of dynamics for internet speed series. The low AIC and absence of significant autocorrelation also suggest a well-behaved model, supporting hypothesis H3 regarding a stable short-term forecast for internet speed.

4.4 Synthesis and Research Contribution

The empirical evidence indicates that internet connectivity in rural areas increases. Hypothesis H1 was strongly supported, showing that internet speeds increase over time. Hypothesis H2 was supported, showing that internet speeds change seasonally but not as strongly as the long-term trend. Hypothesis H3 was supported, showing that despite non-stationarity, short-term forecasting was possible. This paper has provided good evidence for internet development in a developing country through the use of trend estimation, unit roots, and time-series forecasting. It contributes to the field in three main ways: evidence that internet connectivity increases in rural areas and the potential for temporal performance indicators for internet development.

These findings should be considered alongside several limitations. The sample comprises 46 monthly observations from a single aggregated data source (Giga Global Maps), which, while offering consistent longitudinal coverage, has not been cross-validated against independent network-operator or regulator measurements and may be subject to changes in the underlying pool of contributing users or devices over time. The analysis is also limited to a single region (Samarkand) and a single quality metric (average download speed in Mbps); it does not incorporate other dimensions of connection quality such as latency, jitter, packet loss, or upload speed, which are also relevant to user experience and digital-divide assessment. Finally, the relatively short observation window (under four years) constrains the reliability of the estimated seasonal pattern and limits the SARIMA model's validation to a single non-overlapping test period; extending data collection and incorporating additional quality-of-service dimensions and independent data sources are identified as priorities for future work.

4.5 Implications for Applied IT Systems

The results obtained in this study have important implications for developing applied IT systems that should be used for monitoring rural digital infrastructure. It is possible to develop automated quality of service monitoring tools by applying trend estimation and short-term forecasting techniques.

The proposed IT systems could be applied for developing early warning systems, performance benchmarking, and evidence-based digital infrastructure governance, especially in rural areas, where manual monitoring is a costly process.

5 CONCLUSIONS

This study investigated the evolution of internet connectivity in the Samarkand region of Uzbekistan using time-series econometric analysis. The results demonstrate a statistically significant long-term increase in average internet speed, confirming the continuous improvement of rural digital infrastructure. Although seasonal fluctuations were observed, they were considerably weaker than the underlying long-term growth trend, indicating that structural infrastructure development is the dominant factor influencing internet performance.

The forecasting analysis further showed that, despite the non-stationarity of the original series, a parsimonious SARIMA model provides stable short-term predictions. These findings suggest that time-series forecasting techniques can serve as practical tools for monitoring internet service quality and supporting evidence-based decision-making in digital infrastructure management.

The study contributes to the existing literature by providing empirical evidence on the dynamics of rural internet development in Uzbekistan and by demonstrating the applicability of econometric forecasting methods to digital infrastructure assessment. From a practical perspective, the proposed analytical framework can support the development of automated monitoring systems capable of tracking connectivity trends, identifying performance changes, and assisting policymakers in planning future infrastructure investments.

Future research should extend the analysis to multiple regions of Uzbekistan, incorporate additional network quality indicators such as latency, upload speed, packet loss, and jitter, and validate the findings using independent data sources and longer observation periods. Such extensions would improve the robustness of forecasting models and provide a more comprehensive assessment of rural digital infrastructure development.

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