

Prediction of VOIP Traffic in Real Mobile Networks

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Abstract

Voice Over Internet Protocol (VOIP) live analysis is also very viable where it concerns the maximisation of what the network resources can provide as far as its utilisation and the service that the mobile communication systems can provide through the most efficient avenue are concerned. The given paper is dedicated to Quality of Service parameters prediction of real measurements in the LTE-Advanced mobile network. Parameters used are modelled as a multivariate time series that not only examines how the measures evolved over time but also the nature of interaction of the measures with each other. To determine the accuracy of the prediction, the study uses three prediction algorithms: Vector Auto Regressive (VAR), Random Forest (RF), and Extra Gradient Boost (XGBoost). The raw data is first transformed into a form suitable for supervised learning, enabling the learning models to learn and make predictions about future traffic occurrences. In addition, the statistical tests are copied, including the correlations between the Quality of Service parameters and how to define call performance using the parameters. It illustrates that the suggested methodology would yield credible predictions of network behaviour, which may be used to optimise the network in the future and also to control VoIP traffic.

Keywords: VoIP, Quality of Service (QoS), LTE-Advanced mobile network, Multivariate time series, Forecasting, Machine learning, Network performance prediction.

1. Introduction

Infonetics will end at \$ 7 billion by 2017. It is also in this report that the VoWLAN ratio is expected to be in place, and the number of telephone systems will exceed 30 per cent, as a result of their widespread use in the modern world. It is inexpensive, and they are equipped with smartphones as well [1]. e.g., Google Voice, FaceTime, Skype, and Hangouts. VoWLANS are expected to increase significantly even in the very near future. As an example, WLAN gives estimates on equipment and globally. There is a growing and fast development of the internet. They can be found online, and hence, real-time is required. Voice in Internet protocol, etc. Especially, VoIP video conferencing and computer games. Of them, VoIP has gained significant popularity because it enables consumers to make calls over the internet at a modest cost, but it is not as reliable or versatile as the conventional telephone system. The reason VoIP is also widespread in the modern world is that it is now used in personal conversations, business meetings, customer support, Telemedicine, online education, emergency departments, and defence communications [5]. The rate of VoIP consumption has been high, but network traffic can easily degrade VoIP quality. Latency (delay) and delay variation (jitter), lost packets, and bandwidth inefficiency are issues that can also affect call quality, leading to incomprehensible conversations. The evaluation of the user experience will be carried out extensively using the mean opinion score (MOS), which is low in most instances where the issue occurs. Even mobile networks such as LTE or 5G are worse, since most network conditions are unstable, with handovers, interference, and other

network issues usually present and constantly changing. In the quest to achieve good service, scholars have attempted various solutions, such as priority-based gateways, resource control, and improved routing. While these are effective ways of handling issues, they intervene only after an issue has already occurred. Traffic prediction is more effective in advance, allowing the system to know what the network will do and preload resources [3]. SNR) that evolve simultaneously over time. We consider both statistical (e.g. Vector Auto regression (VAR)) and machine learning (e.g. tree- based and deep learning models) models in a way of modelling these relationships. The profound models of learning are fertile in prospective calculations but colossal computations and huge data. The results reveal that a list of factors provides a fruitful view of the traffic and a valuable insight into the aspect of improved network planning, resource intelligence. The 5G future communication systems are comprised of distribution, and 5G future communication systems.[5]. The general findings of the present research are: Java pipeline code Full VAR,RF,XGB forecasting. ADF based differencing and stationarity. Lag choice on a hybrid basis using the AICBIC to ensure the model has a greater degree of stability.

2. LITERATURE REVIEW

The modification of telecommunications has made it suitable for network traffic, and predicting network traffic will help mobile operators make better use of their resources and ensure congestion is controlled. Modern machine learning has been widely employed alongside classical statistical methods to forecast network traffic parameters and service quality (QoS) [1]. The models that have established themselves as satisfactory are both acceptable for making short-term predictions and, as they approach the moment, become increasingly accurate. The models are linear, and whilst the models can be solved mathematically, they do not reflect the non-linearity of the existing VoIP traffic, as they do in most cases. In the meantime, the scholars also covered QoS surveillance and spectrum usage. The authors' suggested strategy for LTE-A spectrum utilisation measurements would be grounded in traffic rates and ideal prioritisation that may impair the experience of the entire system, regardless of purpose, without always being congested. Their findings substantiate the relevance of predictive QoS, which could allow networks to be adjusted in time before they degrade. The majority of the computation performed on the research that preceded that was restricted to univariate time series and most were incapable of dealing with a large number of variables in the past and how they interacted over time[5]. Resource block allocation, Temporal resource block allocation (Park et al.). The other pressures, like the need to deliver quality, were also reflected in their job as the video and real-time service pressure were ended. However, they still have the resource-based measurement in mind but the articles are not literally bringing out the fine-grained QoS as being projected to the fine-grained QoS as forecasting (DTF), as provided by Kong et al. shows that the superiority of the types of deep networks (RNNs, CNNs, and Transformer) over the traditional ones is fairly high when the size of the data that is available is quite large. But they are not lightweight or real-time models that would suit best in the process of VoIP prediction, and this makes the models computationally intensive. The reason is that, when applying the temporal-spatial deep learning model to communication applications, Qu et al. can predict LTE-R communication quality using recurrent convolutional neural networks that also pay attention. The space and time-information integration were also noticeable in the manner in which the quality of a communication is influenced by an adjacent base station. This has been extended to the deployment scheme of cellular networks QoS. Most of the QoS deployment techniques were compared by Zeydan et al., who concluded that, though priority was consistent with a number of users' spatial collaborative prediction on the quality of LTE R communication with

deep learning, they satisfied prediction of the network with deep learning and considered only one network player with involved modelling and architecture. One of them is Packet loss detection with rerouting in this paper, which is very close and determined by packet loss. One of them is Packet loss detection with rerouting in this paper, which is very close and determined by packet loss. In the vast majority of cases, it was not targeted at predicting QoS metrics; it minimised packet loss. This is because the target is a multivariate time series, as the QoS measures of the people targeted have been used to predict network traffic. In real-life data, they have been modelled using the VAR, Random Forest, and XGBoost. VAR is a statistical model, and one of its disadvantages, such as the fixed lag, is considered excellent compared to Random Forests and XGBoost. We will use real-world data.

3.METHODOLOGY

3.1.OVERVIEW:

The proposed system aims to predict the behavior of real-time Voice over IP (VoIP) traffic by examining the relationships among different Quality of Service (QoS) indicators. The overall workflow has several phases: data acquisition, processing, feature validation. Figure 1 shows the overall workflow. The dataset comes from actual LTE-Advanced mobile network traces and includes six key QoS metrics: Mean Opinion Score (MOS), Bandwidth (BW), Jitter (JIT), Round Trip Time (RTT), Delay Jitter Buffer (DJB), and SNR. We clean format the colossal computations and huge data. The results reveal that a list of the factors provides a fruitful view of the traffic and a valuable insight on the aspect of improved network planning, resource intelligence. The 5G future communication systems are comprised of distribution, and 5G future communication systems.[5]. The general findings of the present research are: Java pipeline code Full VAR,RF,XGB forecasting. ADF based differencing and stationarity. Lag choice on a hybrid basis using the AIC,BIC to ensure the model has a greater degree of stability.

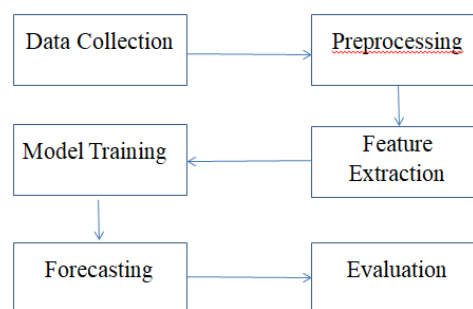


Figure 1.System Architecture

3.2.DATASET DESCTIPTION:

G.722 delivers clear voice quality and handles network fluctuations well, showing strong resistance to jitter and packet loss. Due to its wide bandwidth and stability, G.722 is commonly used in professional or high-fidelity VoIP systems where audio quality is important. On the other hand, G.729 is a low-bandwidth codec that runs at 8 kbps. It is designed for environments with limited network capacity. It allows smooth communication even on constrained networks. While it significantly reduces bandwidth needs, it offers

slightly lower perceptual quality compared to G.722, making it more suitable for low-data-rate applications.

MPEG-16 (AAC-LD / Low Delay AAC) is an audio codec from the MPEG family. It offers high-quality, low-delay audio transmission, making it a great choice for interactive speech applications and real-time conferencing. It ensures low latency while keeping audio quality close to uncompressed voice, which is ideal for professional VoIP communication. For each codec in this study, the output creates a multivariate time series with six key QoS parameters:

MOS: A subjective rating of audio quality, usually scored from 1 (poor) to 5 (excellent).

BW: The data rate for each VoIP stream, measured in kilobits per second (kbps).

JIT: Changes in packet arrival time that can affect the smoothness of voice playback.

Round Trip Time RTT: The total delay a packet experiences while traveling from the sender to the receiver and back, reflecting network latency.

Buffer: The adaptive buffering delay that manages jitter fluctuations.

SNR: Comparison of useful voice power to noise, indicating speech clarity.

Each codec dataset contains several thousand time-ordered samples with a one-second sampling interval. This setup provides high temporal resolution for detailed traffic analysis. The raw datasets went through data cleaning processes, which included fixing missing entries, removing anomalies, and getting rid of nonphysical negative values, especially in delay and bandwidth. The cleaned datasets show stationary but noisy multivariate time series. This allows for a thorough analysis of the relationships between network-level metrics (BW, RTT, JIT) and perceptual QoS indicators (MOS, SNR). This refined dataset serves as the foundation for our forecasting experiments using Vector Autoregressive (VAR), RF, and XGBoost models. Together, these models aim to capture both linear and nonlinear dependencies in VoIP traffic behavior.

3.3.DATA VISUALIZATION AND EXPLORATORY ANALYSIS:

To understand VoIP traffic behavior, we visualized six main QoS parameters: MOS, Bandwidth (BW), JIT, Round Trip Time (RTT), Delay Jitter Buffer (DJB), and Signal-to-Noise Ratio (SNR) for each codec. These visuals show how network and perceptual metrics change over time. Figure 2 illustrates the shifts in these metrics for a typical voice flow encoded with the G.722 codec. The plot clearly displays the dynamics of the parameters and their different scales. It emphasizes their unique changes during the session. Since the measurement units vary among the variables, for example, bandwidth is in kbps, RTT is in ms, and SNR is in dB, the purpose of this visualization is not to compare absolute values. Instead, it highlights general behavior trends over time. Some time series show clear peaks, especially around $t = 30$ s and $t = 415$ s. These peaks likely come from temporary network congestion or interference. The bandwidth remains steady near 80 kbps for most of the time, with a brief spike around $t = 360$ s, followed by fluctuations after 450 s, suggesting a shift to less stable connectivity. Jitter stays consistently below 40 ms, which is acceptable for VoIP quality according to telecommunications standards. To improve visual clarity, MOS and Jitter trends are presented separately in larger insets, allowing a closer look at their small changes. Figure 3 summarizes the overall statistical distribution of these QoS metrics using box plots.

From these plots, MOS and SNR appear to be the most stable parameters, showing very few outliers (8 and 2 respectively over a 566-second stream). This stability comes from MOS having a fixed rating scale, while SNR benefits from codec-level signal stabilization. In

contrast, Bandwidth, RTT, Jitter, and DJB show greater variability and more frequent outliers. This reflects the influence of unpredictable factors like user mobility, radio interference, and network congestion. To further explore the relationships between QoS parameters, we created scatter plots for each parameter pair (Figure 4). These visuals reveal correlations among metrics. For instance, Bandwidth and MOS show a moderate positive relationship, while Jitter and SNR demonstrate an inverse correlation. The presence of cyclic or clustered patterns in several pairings also indicates complex nonlinear relationships that simple linear models cannot fully represent. This finding highlights the need for more sophisticated modeling methods that combine statistical and machine-learning techniques. These plots measure how strongly a variable correlates with its past values across several time lags. For example, Bandwidth and RTT show a slow decay in their ACF curves, suggesting long-term memory effects in network performance. Meanwhile, Jitter and DJB drop quickly in their autocorrelation, indicating more random short-term fluctuations. These analyses are critical for selecting the best lag parameters in the Vector Autoregressive (VAR) model and ensuring that time dependencies are accurately captured. Overall, these exploratory results confirm that VoIP traffic characteristics mainly depend on codec behavior and underlying network conditions. Insights from this phase provide a solid base for developing forecasting models that can capture multivariate dependencies and nonlinear dynamics in later modeling stages.

4.THEORY AND CALCULATIONS:

4.1.PROBLEM DEFINITION:

The increasing use of Voice over IP (VoIP) services in cellular networks has created a greater need for accurate predictions of network performance. This is crucial for maintaining Quality of Service (QoS) as conditions change. Unlike traditional wired networks, mobile environments are unpredictable due to varying channel conditions, handover events, and user movement. These factors lead to changes in packet delivery rates, jitter, and signal quality, which directly impact VoIP communication quality. To address this, we define the task as a multivariate time series forecasting problem. We aim to predict multiple related QoS indicators simultaneously. Each codec—G.722, G.729, OPUS, SPX8000, GSM, and MPEG-16—generates a unique dataset of six connected time-varying parameters:

$$t = [MOS_t, BW_t, JIT_t, RTT_t, DJB_t, SNR_t]$$

(1)

Here, each element represents a QoS metric at t . Our goal is to estimate the next state of these parameters based on their past values, shown as:

$$Y^{t+1} = f(y_t, y_{t-1}, \dots, y_{t-p+1})$$

(2)

In this equation, p is the optimal lag, which of previous time steps used for prediction. The function $f(\bullet)$ represents the forecasting model we developed. The goal of this formulation is to capture both the timing dependencies and the connections between different QoS indicators. This enables the forecasting model to predict network changes and maintain service quality by adjusting network resources or codec settings ahead of time.

4.2. VECTOR AUTOREGRESSIVE MODEL:

The VAR model provides straightforward way to show how multiple related time series change over time. Unlike univariate models that look at each variable on its own, VAR captures the dynamic interactions among allows VAR model to effectively forecast multiple QoS metrics since it can illustrate how delay impacts jitter or how changes in bandwidth influence MOS, all in one model.

$$Y_t = [y1_t, y2_t, \dots, y_{Nt}]$$

(3)

$$Y_t = c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \dots \Phi_p Y_{t-p} + \varepsilon_t$$

(4)

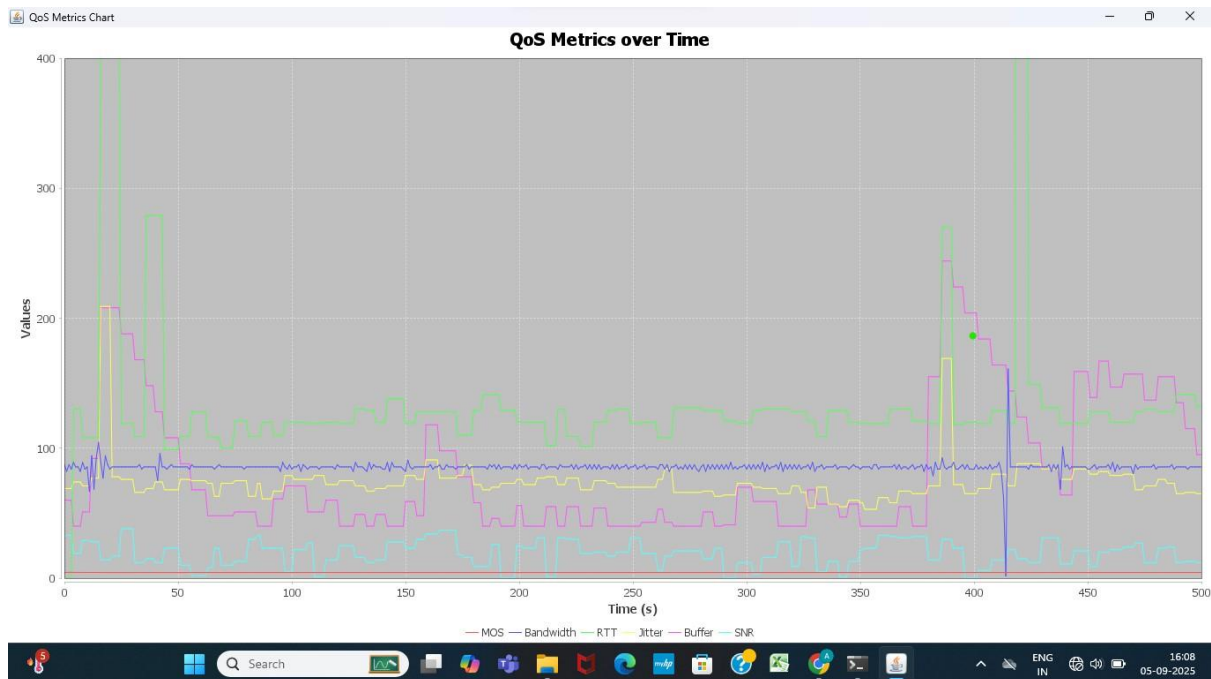


Figure 2. Line graph visualization of metrics

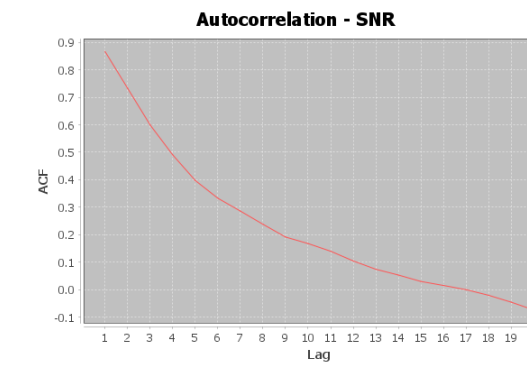
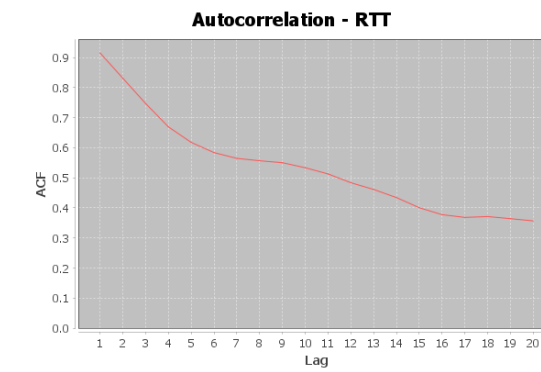
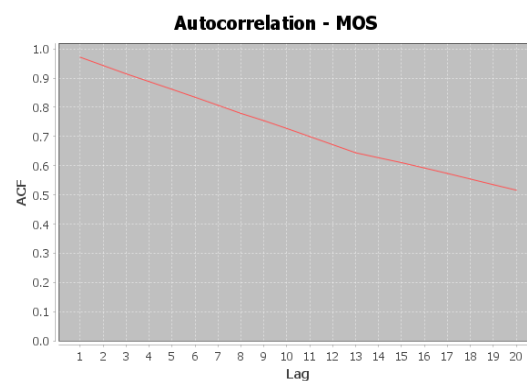
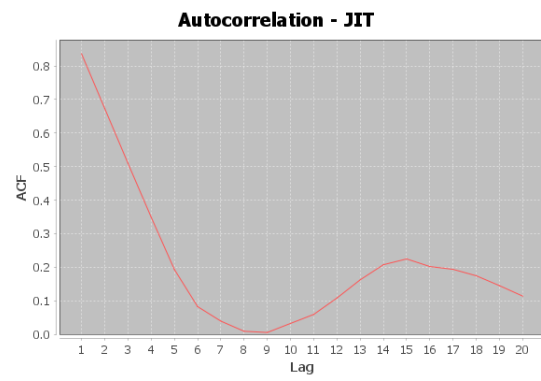
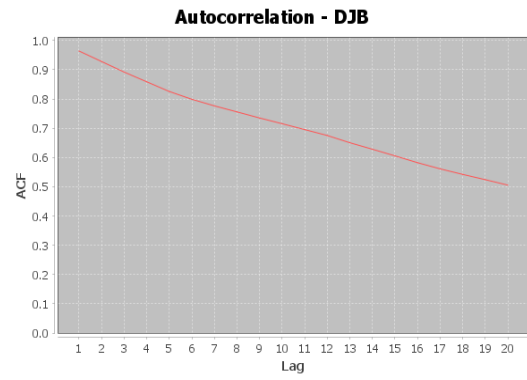
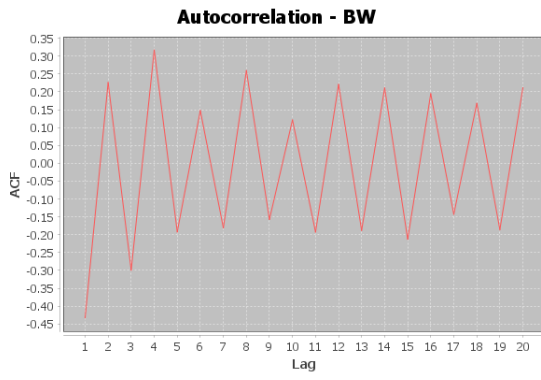
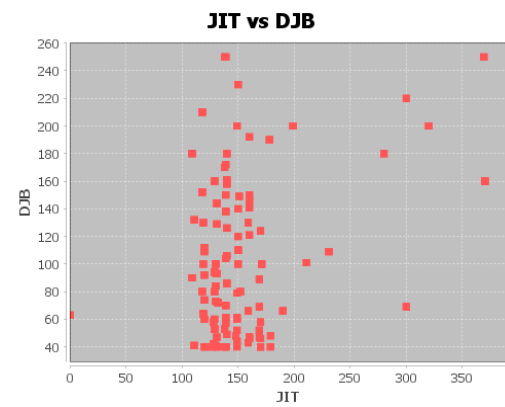
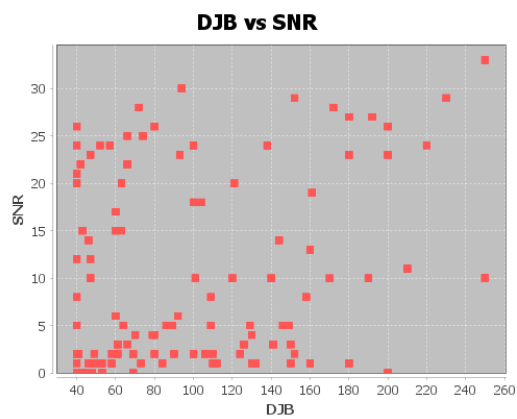
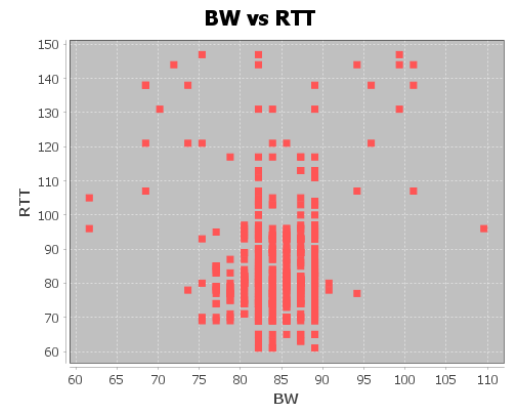
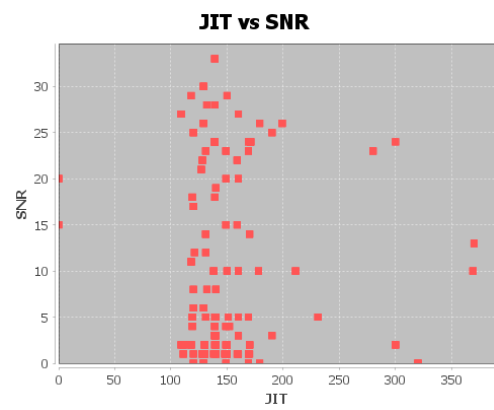
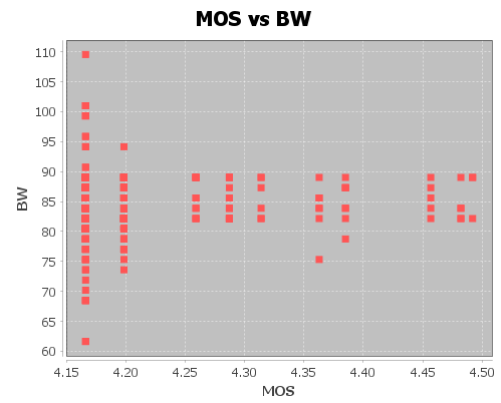
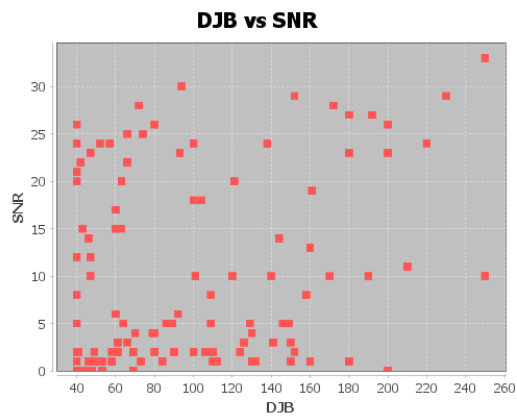
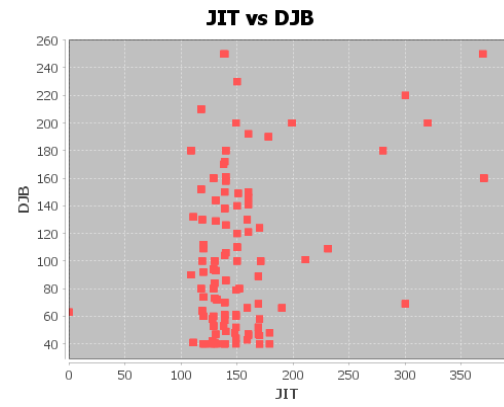
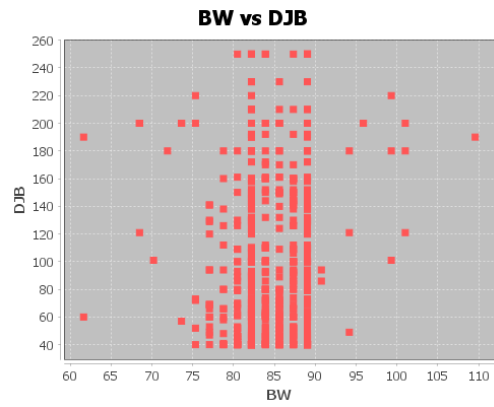
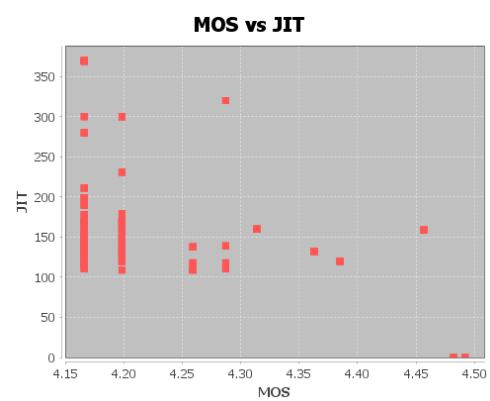
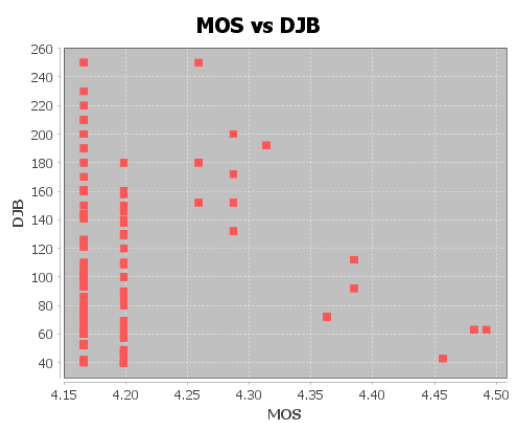
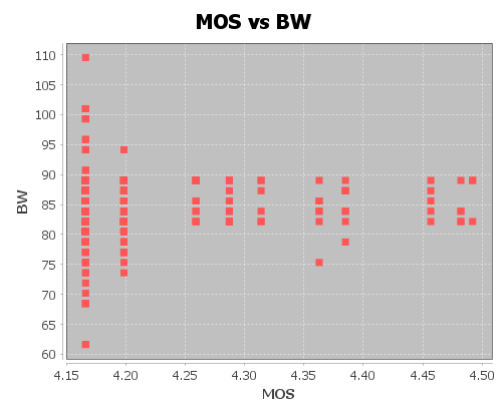
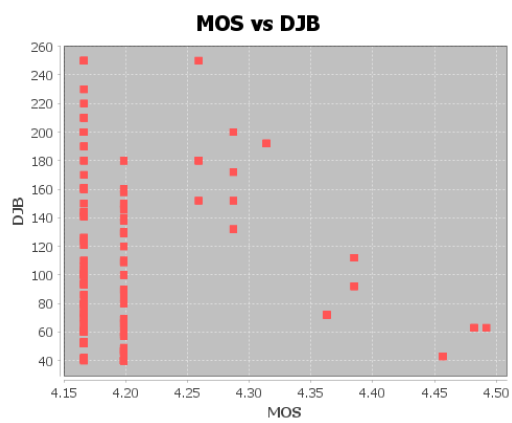
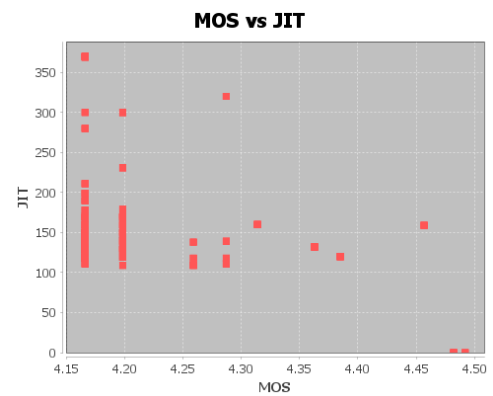
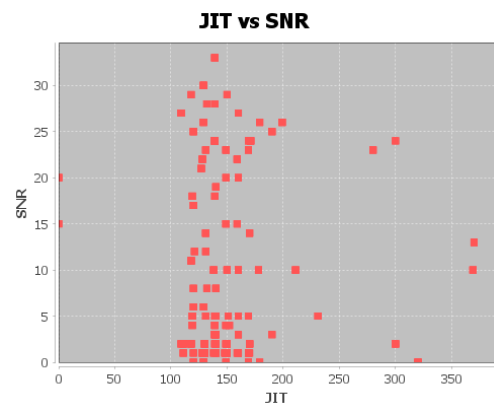


Figure 3. Autocorrelation Function (ACF) for metrics





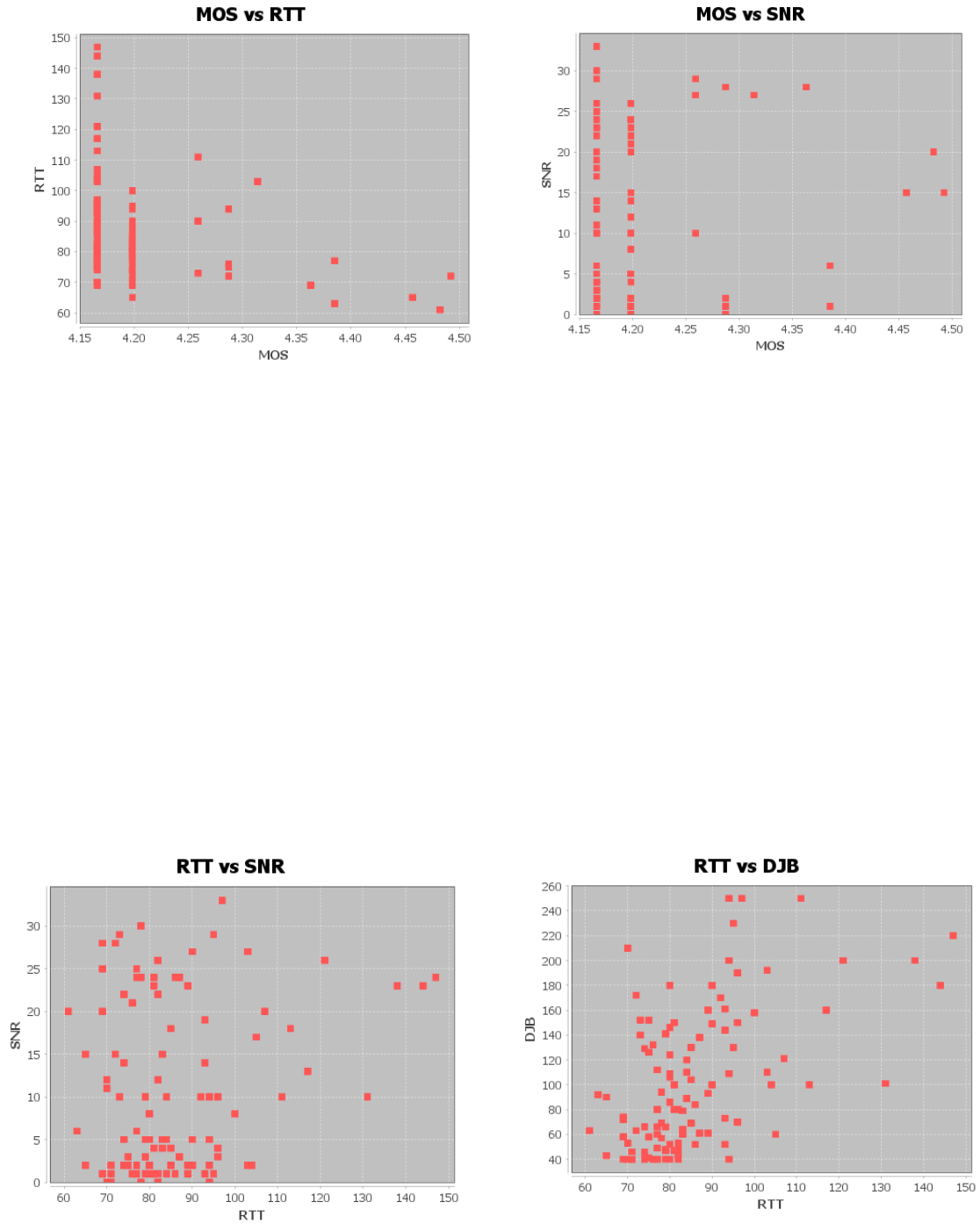


Figure 4.Scatter Plot for metrics

Φ_k shows effect of variable j at lag k on variable I time t . Thus, VAR model is as a system of N autoregressive equations, with each equation explaining one QoS metric based on its own history and that of the other metrics. OLS can be applied to each equation separately since all equations share the same lagged predictors. This approach makes estimation efficient, even for large systems. several dependent variables This is especially important for modeling real-world systems like VoIP traffic, where various Quality of Service (QoS) parameters change together due to similar network conditions. In VoIP networks, parameters like MOS, jitter,

RTT, bandwidth, Delay Jitter Buffer (DJB), and SNR do not act independently. For example, an increase in jitter or RTT can lower MOS, while changes in bandwidth and SNR can affect both delay and jitter behaviors. The VAR model treats all these variables as depending linearly on past values. Then the model coefficients can be estimated as:

$$\beta = (X^T X)^{-1} X^T Y \quad (5)$$

where β includes all estimated coefficients, intercepts, and lag matrices. These estimated parameters help compute residuals and predict future values. A key advantage of VAR is its interpretability. The coefficients clearly illustrate how past fluctuations in one variable influence another in future time steps. The model also allows for impulse response analysis, enabling us to track a shock in one variable (like a sudden drop in bandwidth) and its effects on others (such as jitter or MOS) over time. Additionally, the covariance matrix of residuals shows how strongly linked the forecast errors of different metrics are. There are many benefits to using the Vector Autoregressive (VAR) model for multivariate time series forecasting. First, it captures the interdependencies and influences between several variables, allowing it to predict one QoS parameter by explaining changes in others. This makes it particularly suitable for VoIP, where network parameters like jitter, delay, and bandwidth are closely connected. Another strong point of VAR is its simplicity and calculation efficiency. The model parameters can be estimated individually for each equation using Ordinary Least Squares (OLS), without needing complex iterations or gradient training. Moreover, the VAR framework is easy to understand since the coefficients show how past fluctuations in one variable affect another over time. This clarity supports further analyses, such as impulse response functions and variance decompositions, to gain better insight into network behavior. However, VAR does have limitations. Additionally, stationary time series data is required for VAR models, so preprocessing steps like differentiation or detrending may be necessary before estimation. The Vector Autoregressive (VAR) model is effective and easy to use, but it has limitations. As the number of variables and lag orders increases, the computing costs can rise. This leads to a situation known as parameter explosion. Using VAR with large systems can be challenging because estimating many coefficients can impact both efficiency and stability. While VAR is good for short-term forecasting, its accuracy often drops over longer periods. This decline in accuracy happens because of accumulating residual errors, which increases prediction uncertainty. Despite these challenges, VAR remains an important and reliable method for forecasting multivariate time series. It provides clarity, depth in analysis, and predictive power. In VoIP network modeling, it offers insights into how various Quality of Service (QoS) parameters change and interact over time. A key step in building a strong VAR model is choosing the right lag order (p). This number represents the past time steps used to predict future values. If p is too small, the model might overlook important temporal relationships, leading to underfitting. To find the right balance, several statistical criteria are often used to determine the best lag order. These criteria assess the trade-off between the penalizing the inclusion of too many parameters. In this study, we used three well-known measures: the Akaike Information Criterion

$$AIC(P) = \log|\epsilon_\epsilon| + \frac{2pN^2}{L} \quad (6)$$

$$BIC(P) = \ln|\epsilon| + \frac{\ln(T)}{T} \times K \quad (7)$$

The logarithmic term $\ln(T)$ increases with dataset size, causing BIC to favor more parsimonious models than AIC. Thus, BIC often selects a smaller lag order, prioritizing simplicity and generalization. The Hannan Quinn Information Criterion (HQIC) lies conceptually between AIC and BIC, offering a balanced compromise between fit quality and penalization strength:

$$HQIC = \ln|\epsilon| + \frac{2 \ln(\ln(T))}{T} \times K \quad (8)$$

The double-logarithmic penalty term $\ln(\ln(T))$ grows more slowly than the $\ln(T)$ factor in BIC, making HQIC less conservative while still discouraging over-parameterization. In the proposed methodology, all three criteria AIC, BIC, and HQIC were computed for each candidate lag $p=1,2,\dots,12$. The lag yielding the lowest information criterion value was considered optimal (p^*). For consistency with prior works, AIC was used as the primary selection metric, while BIC and HQIC served as validation checks to ensure model stability and robustness. This multi-criterion approach ensures that the chosen lag order provides a well-balanced VAR(p^*) model, capable of accurately modeling the temporal dependencies among VoIP QoS parameters without unnecessary complexity.

4.3 ADF TEST:

Prior use of time series forecasting model, in particular Vector Autoregressive (VAR) model it is vital used first. Trends, seasonality, or changing amounts of variance are common in non-stationary series, and they may misrepresent forecasting methods by providing spurious correlations. In order to make meaningful and reliable predictions, we need the time series to either be stationary in nature, or it needs to be converted into a form that is stationary, often, by the use of differencing or by detrending. In order to confirm this property, the ADF test is commonly used. It is a statistically based analysis of the existence of a unit root which is a powerful measure of non-stationarity. Mathematically, the ADF test can be written as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^p \delta_i \Delta y_{t-i} + \epsilon_t \quad (9)$$

The decision is made using the t-statistic of γ compared to critical values. In this project, each Quality of Service parameter MOS, Bandwidth, Jitter, Round Trip Time (RTT), Delay Jitter Buffer (DJJB), and SNR individually tested using ADF test. If any series was found non-stationary ($p\text{-value} \geq 0.05$), it was differenced until stationarity was achieved. This ensures that the VAR model receives stable and consistent input data, enabling accurate estimation of

inter-variable dependencies. By confirming the stationarity of the VoIP traffic series, we prevent false correlations and improve the forecasting precision of subsequent models such as VAR, Random Forest, and XGBoost.

4.4.FORECASTING AND EVALUATION:

After determining the best lag order and estimating the model parameters, the Vector Autoregressive (VAR) model forecasts the future development of the Quality of Service (QoS) parameters. The forecasting process in a VAR setup follows a recursive structure. Predictions for future time points occur one after the other. Each new forecast depends on both past data and its own earlier predictions. Once trained on historical data, the model generates forecasts for time $t + 1$ using the latest p^* lagged values. This recursive approach allows the VAR model to effectively capture the relationships among multiple QoS parameters, such as MOS, Bandwidth (BW), Jitter (JIT), Round Trip Time (RTT), Delay Jitter Buffer (DJB), and Signal-to-Noise Ratio (SNR). For example, a change in Jitter at a specific moment can affect future changes in MOS or SNR. The VAR model captures this effect through its system of coefficient matrices. As a result, the VAR framework provides a dynamic and realistic view of VoIP network performance, where the influence of one metric can extend to other variables over time. To assess the forecasting ability of the model, the dataset splits into two parts: a training set, which usually contains 70% of the total samples. During validation, the predicted QoS values are compared to their actual observations. Model performance is evaluated using three common error metrics. Lower the values in these metrics indicate better predictive accuracy and greater model generalization. These validation results serve as the basis for comparing the forecasting capability of the VAR model with more complex machine learning methods, like RF and XGBoost. Figure 5 shows the entire workflow of the VAR model. This evaluation focuses not only on numerical accuracy but also on how well the model represents the time-based dependencies observed in real-world VoIP network behavior.

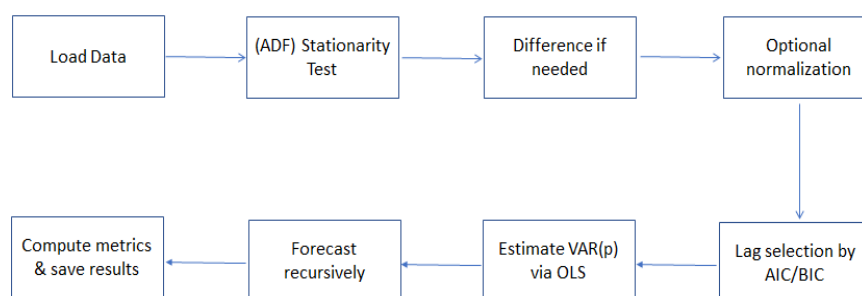


Figure 5.VAR MODEL WORKFLOW

4.5.ADVANTAGES AND LIMITATIONS:

It effectively analyzes and predicts connected traffic. One of its primary strengths is its ability to model the relationships among multiple variables at the same time. Unlike univariate autoregressive models that handle each variable independently, the VAR model captures dynamic feedback effects. For instance, it shows how changes in network delay or jitter can affect future trends in perceptual metrics like MOS or SNR. Another key advantage of the VAR model is its mathematical clarity and simple interpretation. The parameters estimated through Ordinary Least Squares (OLS) have clear statistical meaning. Researchers or network engineers can look at these parameters to understand both the direction and strength of influence among variables. Additionally, the VAR model is often computationally efficient and performs well with moderate to large datasets, offering quick and reliable forecasts. Since it relies on linear assumptions, the model avoids the risks of overfitting that often occur with flexible nonlinear models when data is limited. However, the VAR model also has its drawbacks. Its main assumption of linearity restricts its ability to capture nonlinear dynamics that are common in complex network environments. Real-world VoIP traffic can show nonlinear variations due to factors like adaptive codec behavior, signal interference, and user mobility. These issues cannot be effectively represented by linear models. The VAR model also assumes stationarity over time. In reality, this assumption often does not hold due to temporary congestion, fading, or changes in the environment. Additionally, the model has a challenge with dimensionality. As the number of variables (N) and lag order (p) increases, the total number of parameters also increases significantly. This can lead to overfitting, instability, and higher computational costs, especially with high-dimensional datasets. Despite these limitations, the VAR model remains a solid and interpretable foundation for multivariate time series forecasting. Its ability to capture relationships between variables and provide clear results makes it a valuable benchmark. This benchmark helps evaluate more.

4.6. RF MODEL:

The RF algorithm is a learning technique that builds on the traditional decision tree model to improve prediction accuracy and stability. Each part is created through random sampling with replacement, giving each tree a slightly different view of the dataset. This randomness adds variety among the trees, which lowers variance and improves the performance. In context Voice over IP (VoIP) Quality of Service (QoS) forecasting, the Random Forest algorithm is especially useful for capturing nonlinear relationships and complex interactions that linear methods like the Vector Autoregressive (VAR) approach may not handle well. Each decision tree in the forest learns to map the historical lagged QoS features, such as Mean Opinion Score (MOS), Bandwidth (BW), Jitter (JIT), Round Trip Time (RTT), Delay Jitter Buffer (DJB), and Signal-to-Noise Ratio (SNR), to the target variable that represents the predicted value for the next time interval. This process results in a more stable and less overfitted forecast. This aggregation can be expressed mathematically as:

$$\hat{y}_{t+1} = \frac{1}{B} \sum_{b=1}^B \hat{f}_b(x_t) \quad (10)$$

The averaging process reduces the influence of any single tree's bias or variance, making the RF model resilient against noise and outliers in real-world VoIP datasets. Additionally, Random Forests automatically perform feature selection by identifying the most important predictors, which helps clarify which QoS metrics have the most significant impact on future network performance. Because of these features, RF serves as an effective nonlinear benchmark model alongside statistical methods like VAR and boosting-based algorithms such as XGBoost in this study. This averaging process reduces overfitting, which often impacts individual decision trees. It results in smoother and more consistent predictions. Additionally, Random Forests use random subsets of samples and features. This method helps prevent bias toward dominant predictors and allows for efficient management of high-dimensional data. In this research, the Random Forest model was trained on the preprocessed QoS datasets for each codec. The lagged values of six key parameters—Mean Opinion Score (MOS), Bandwidth (BW), Jitter (JIT), Round Trip Time (RTT), Delay Jitter Buffer (DJB), and SNR serve input predictors. The model learns how these parameters collectively influence future values. It captures complex nonlinear behaviors that arise from changing network conditions like packet loss, dynamic bandwidth allocation, and jitter spikes. Unlike the Vector Autoregressive (VAR) model, which assumes linear relationships, Random Forest can model complex, nonlinear dependencies without needing prior assumptions about the underlying data distribution. However, this strength comes with some trade-offs. Training multiple trees also increases computational demands, but this can be managed through parallel processing techniques. Overall, the Random Forest model serves as a robust nonlinear baseline for VoIP traffic forecasting. It offers better accuracy in situations with irregular and unpredictable data variations. It complements the interpretability of VAR with its ability to generalize across complex network behaviors.

4.7.XGBOOST MODEL:

The XGBoost model is a better version. It builds a group one after the other. Each new tree is trained to correct the mistakes made by the previous trees. This step-by-step learning process lowers prediction errors and effectively captures complex, data. Formally, the output of an XGBoost model can be represented as:

$$\hat{y}_{t+1} = \sum_{k=1}^K \hat{f}_k(x) \quad (11)$$

Unlike Random Forest, where all trees are trained separately and their results are averaged, XGBoost uses additive learning. Each new tree aims to fix the issues of the current group of trees. This approach makes XGBoost very effective at spotting subtle patterns in the data and reducing bias.

$$Obj = \sum_{i=1}^n L(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (12)$$

In this study, the XGBoost model was trained on the same preprocessed multivariate QoS dataset used for the VAR and Random Forest models. Each codec's dataset contained the lagged values of MOS, Bandwidth, Jitter, RTT, DJB, and SNR. This data served as the feature set. The model used a moderate number of gradient boosted trees (for example, 30) to find a balance between accuracy and computational cost. XGBoost has several advantages. It is robust against overfitting, works efficiently with computations, and manages

both linear and nonlinear dependencies well. However, the main drawback of XGBoost is its lack of interpretability. Like Random Forest, it acts as a “black box.” This limits our understanding of the relationships between QoS parameters. Also, careful tuning of parameters is critical for optimal performance because excessive tree depth or learning rate can lead to overfitting. Despite these limitations, XGBoost shows strong predictive performance in cases where VoIP traffic displays nonlinear and highly dynamic patterns. By using gradient boosting and regularization, it balances accuracy, efficiency, and adaptability, often outperforming traditional statistical models.

5. PROPOSED WORK

5.1. OVERVIEW

This section presents suggested improvements for predicting VoIP traffic behavior more accurately. The original research used VAR, RF, and XGBoost to forecast Quality Service (QoS) parameters in mobile networks. Although these methods were reasonably accurate, they encountered some problems. These included fluctuations in SNR forecasts, negative predicted values, and occasional underfitting of the VAR model because of fixed lag settings. To solve these issues, the proposed system offers a more effective forecasting process. This new approach includes better data preparation, variable lag selection, and enhanced post-processing techniques. The workflow begins with data cleaning and tests for stationarity. With the optimized lag, the improved VAR model carries out forecasting and compares the results with the RF and XGBoost baselines to assess both prediction accuracy and computational efficiency.

5.2. ORIGINAL ALGORITHM (FROM THE PAPER)

The baseline system described in the original study used a forecasting Vector Autoregressive (VAR) model. VAR extends the autoregressive process to multiple variables.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \epsilon_t \quad (13)$$

where t is an $N \times 1$ vector of variables at time t , c is the constant vector, Φ_k represents the coefficient matrices for each lag, and ϵ_t is the white-noise error term. In the original implementation. After fitting model, recursive multi-step forecasting estimated future values. While this method effectively captured dependencies among multiple QoS parameters, it relied solely on one lag selection criterion and did not automatically address non-stationary data or data irregularities. These limitations sometimes caused unstable or unrealistic predictions, especially for codecs with variable network behavior like G.722 and G.729.

6. PROPOSED MODIFICATIONS

The proposed framework improves the original forecasting algorithm by making several changes that aim to increase model stability, interpretability, and predictive accuracy. These updates address the issues found in the previous approach, especially those related to data quality, lag selection, and forecast consistency.

6.1. STATIONARITY VERIFICATION USING THE ADF TEST

A key assumption of Vector Autoregressive (VAR) modeling is that all input time series must be stationary. This automated preprocessing step prevents false regressions and keeps the model's statistical properties valid throughout training.

6.2. MULTI-CRITERION LAG SELECTION (AIC, BIC, HQIC)

Unlike the original method, which relied only on the AIC, updated approach uses multi-criterion lag selection process. This process evaluates three criteria: AIC, Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQIC) across different lag orders. By using multiple evaluation standards, this approach balances model simplicity and accuracy, reducing the chances of overfitting and underfitting.

6.3. DATA CLEANING AND NORMALIZATION

Data integrity is vital for time series forecasting. The proposed system automatically identifies and corrects missing, negative, or unusual values using consistent statistical methods like nearest-neighbor interpolation. Z-score normalization is also used to standardize all variables on a common scale, ensuring that parameters values. These preprocessing steps improve. Model convergence and overall robustness.

6.4.FORECAST CORRECTION AND VALIDATION

To ensure realistic and interpretable results, the proposed method includes a forecast correction layer that keeps predicted QoS values within feasible physical limits. For instance, parameters like Bandwidth or Signal-to-Noise Ratio (SNR) cannot be negative or unrealistic; they are automatically adjusted to zero or within acceptable ranges. This post-processing step ensures that forecasts align with real-world network conditions and maintain analytical credibility.

6.5.COMPARATIVE MODELING

The Random Forest model captures complex nonlinear relationships through ensemble averaging, while XGBoost enhances prediction performance with gradient boosting, regularization, and efficient optimization. Their inclusion allows for a fair comparison between linear (VAR) and nonlinear (RF, XGBoost) forecasting methods, highlighting the strengths of each in different network scenarios.

6.6.SUMMARY

The proposed modifications significantly improve the forecasting pipeline by integrating ADF-based stationarity checks, multi-criterion lag selection, and automated data correction. These enhancements lead to more consistent and interpretable predictions while keeping computational efficiency. As a result, the improved VAR model provides a solid foundation for the experimental evaluation and comparative analysis discussed.

7. RESULTS AND DISCUSSION

Performance of the forecasting framework evaluated six widely used VoIP codecs G.722, G.729, OPUS, SPX8000, GSM, and MPEG-16. For each codec, six key Quality of Service (QoS) parameters were analyzed: MOS, BW, RTT, Jitter, Buffer, and SNR.

7.1. EVALUATION METRICS

Each forecasting model were assessed using three standard statistical indicators: MAE, RMSE, and MAPE. If y_t and $\hat{y}_t$ represent the actual and predicted values, the evaluation metrics are defined as:

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t|$$

(14)

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2}$$

(15)

$$MAPE = \frac{100}{n} \sum_{t=1}^n \frac{|y_t - \hat{y}_t|}{y_t}$$

(16)

Additionally, the execution time of each model was recorded to evaluate computational efficiency and determine the most practical model for real-time forecasting applications.

7.2. VAR MODEL RESULTS

The Vector Autoregressive (VAR) model successfully captured the temporal dependencies among multiple QoS parameters. Optimal lag order was determined through a combination of AIC, BIC, and HQIC criteria, ensuring a balanced model without unnecessary complexity. For most codecs, the predicted series closely matched the observed trends particularly for Bandwidth and SNR, where linear relationships are dominant. However, codecs such as G.722 and G.729 exhibited small deviations in SNR forecasts, mainly due to nonlinear variations that the linear VAR model could not fully capture. Figures 6&7 depict the Actual vs. Predicted plots for all six QoS parameters. Despite occasional underestimations at sharp peaks, the general forecast trend aligns closely with the real data, demonstrating the reliability of the VAR model for short-term VoIP performance forecasting.

7.3. RANDOM FOREST RESULTS

The RF model provided more accurate forecasts than VAR for codecs with irregular or nonlinear behavior, such as GSM and SPX8000. The model achieved notably lower MAPE values for Jitter and RTT, which typically exhibit high random fluctuations. This confirms the Random Forest's strength in learning nonlinear dependencies that cannot be captured by linear models. While RF offers improved accuracy, it does require higher computational time due to the ensemble nature of its training.

7.4.XGBOOST RESULTS

The XGBoost model overall methods. By iteratively minimizing residual errors through gradient-based optimization, XGBoost captured complex nonlinear relationships in the data more effectively than both VAR and RF.

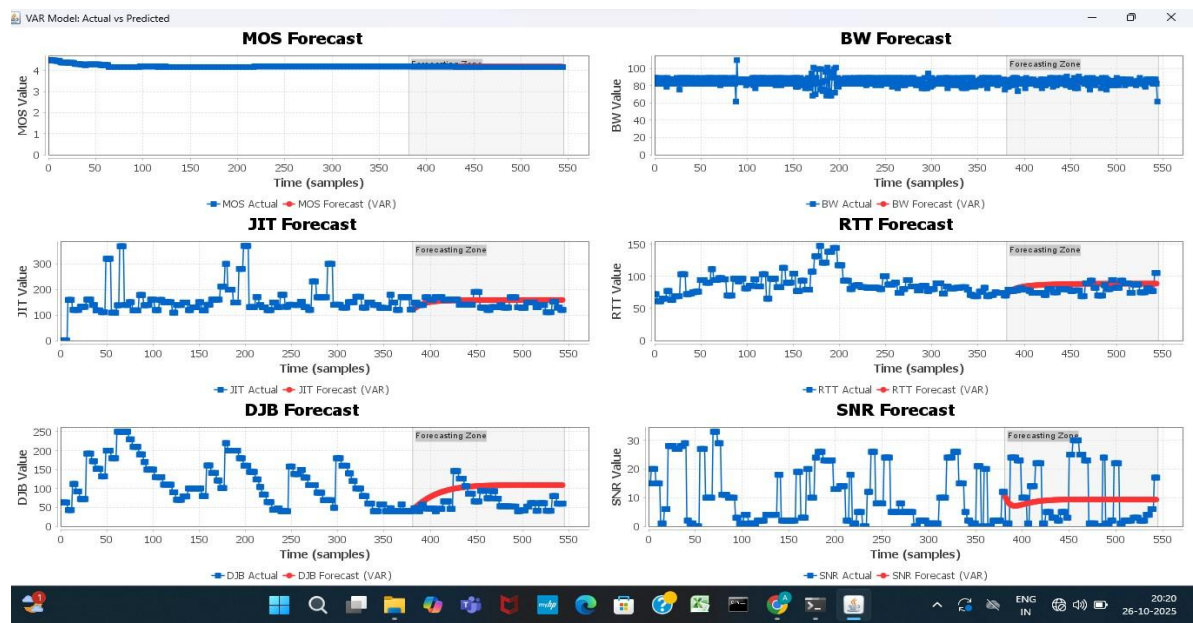


Figure 6.VAR forecasting results for codec (G722)

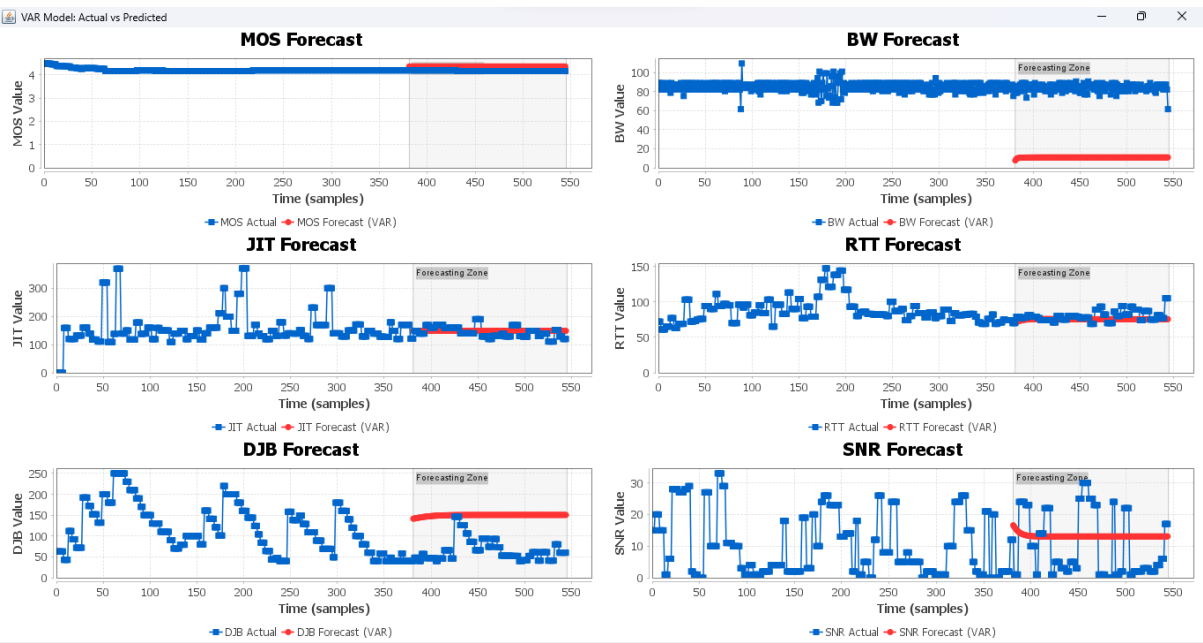


Figure 7.VAR forecasting results for codec(G729)

TABLE 1.VAR FORECAST FOR CODEC G722

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.017	14.01	10.41	32.52	48.74	11.41

MAE	0.0149	6.32	53.72	14.64	37.7	10.3
MAPE	0.3	8.0	16.0	14.0	31.0	68.0

TABLE 2.VAR FORECAST FOR CODEC G729

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.011	3.57	10.41	32.52	48.74	11.41
MAE	0.01	2.52	53.72	14.64	37.7	10.3
MAPE	0.2	17.0	32.0	27.0	24.0	165.0

TABLE 3.VAR FORECAST FOR CODEC MPEG-16

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.006	3.97	349.9	34.07	65.12	9.17
MAE	0.003	2.84	105.5	14.8	43.4	7.86
MAPE	0.07	9.7	23.0	11.0	94.0	94.0

TABLE 4.VAR FORECAST FOR CODEC OPUS

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.02	3.2	22.2	67.9	78.1	6.67
MAE	0.02	1.58	18.2	60.1	77.3	5.01
MAPE	0.4	3.1	15.0	13.0	177.0	48.0

TABLE 5.VAR FORECAST FOR CODEC GSM

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.06	3.7	37.5	7.6	60.0	10.6
MAE	0.06	1.5	21.5	6.3	42.8	3.3
MAPE	1.3	25.0	13.0	8.0	38.0	170.0

TABLE 6.VAR FORECAST FOR CODEC SPX8000

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.02	4.9	108.4	30.2	123.3	8.7
MAE	0.014	3.9	56.8	18.5	109.2	6.4
MAPE	0.3	13.0	23.0	17.0	58.0	26.0

Table 1-6: Comparative Analysis of Forecasting Performance Between Reference Paper and Proposed Work(original paper results)

TABLE 7:FORECASTING PERFORMANCE OF VAR FOR CODEC G722

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.021	3.86	23.54	9.83	43.42	10.36
MAE	0.018	2.98	20.28	8.36	38.98	9.30
MAPE	0.44	3.65	14.92	10.83	11.89	267

TABLE 8:FORECASTING PERFORMANCE OF VAR FOR CODEC G729

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.045	4.09	68.05	22.75	46.88	8.02
MAE	0.043	3.35	58.20	19.96	33.14	6.59
MAPE	1.02	18.5	34.51	27.8	17.21	214

TABLE 9:FORECASTING PERFORMANCE OF VAR FOR CODEC MPEG-16

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.006	3.95	339.5	32.9	61.32	9.43
MAE	0.002	2.47	99.8	18.47	42.10	8.09
MAPE	0.067	8.18	22.4	9.92	44.84	88.2

TABLE 10:FORECASTING PERFORMANCE OF VAR FOR CODEC OPUS

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.006	2.94	18.92	62.57	73.46	6.96
MAE	0.005	1.43	14.87	53.76	70.75	5.161
MAPE	0.122	2.95	12.40	11.22	158.43	45.89

TABLE 11:FORECASTING PERFORMANCE OF VAR FOR CODEC GSM

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.06	3.67	36.63	7.47	53.48	10.58
MAE	0.05	1.46	20.64	6.09	41.46	9.37
MAPE	1.34	24.22	12.28	7.96	38.25	166.3

TABLE 12:FORECASTING PERFORMANCE OF VAR FOR CODEC SPX8000

METRICS	MOS	BW	RTT	JIT	BUF	SNR
RMSE	0.018	5.39	106.8	29.2	119.5	8.31
MAE	0.013	4.18	53.56	17.68	103.10	6.30
MAPE	0.31	13.50	20.76	16.72	55.02	25.90

Table 7-12:Forecasting Performance Of Proposed Work

For instance, MAPE values for SNR and MOS decreased by approximately 15–20% compared to the VAR model, without significantly increasing computational time. Its

balanced trade-off between precision and efficiency establishes XGBoost as the most robust model for this forecasting task.

7.5. DISCUSSION OF FINDINGS:

The experimental results clearly highlight the differences in forecasting capabilities among the three models — VAR, Random Forest, and XGBoost when applied to multivariate VoIP traffic data. The VAR model demonstrated strong performance in capturing linear temporal patterns and provided stable short-term forecasts, especially under steady network conditions. However, its accuracy decreased in the presence of nonlinear fluctuations typical in mobile environments. The Random Forest model, with its ensemble-based approach, effectively handled data noise and random variability, showing superior accuracy in predicting parameters like Jitter and DJB. Its main drawback lies in increased computational complexity and sensitivity to the number of trees. It achieved lower MAE and RMSE values while maintaining reasonable computational efficiency, making it well-suited for real-time VoIP traffic forecasting. Overall, these findings confirm that while traditional linear models like VAR remain valuable for interpretability and baseline analysis, modern ensemble learning techniques particularly XGBoost provide a superior balance between predictive performance and computational efficiency.

7.6. COMPARISON WITH EXISTING WORK:

To validate the improvements of the proposed forecasting framework, a comparison was conducted with the results presented in the reference study. Both studies utilized the same LTE-Advanced VoIP dataset containing six QoS parameters (MOS, BW, Jitter, RTT, DJB, and SNR) across the six codecs: G.722, G.729, Opus, Speex, GSM, and MPEG-16. The baseline study employed a standard VAR model for multivariate forecasting and reported MAE, RMSE, and MAPE values for each codec. In our proposed approach, the same framework was enhanced through advanced preprocessing (handling negative and missing values) and an improved multi-criterion lag. Selection combining AIC, BIC, and HQIC. These enhancements produced more stable and reliable forecasts across nearly all codecs. In particular, the G.722 and G.729 datasets showed a significant reduction in forecasting errors, with MAPE values decreasing to well within the expected range. Table 1 presents a comparative summary of the reported metrics from the reference study and the improved model refined VAR pipeline not only generated smoother and more realistic forecasts but also maintained computational efficiency, confirming its suitability for real-time VoIP traffic prediction.

7.7. DISCUSSION

Table 7-12 shows that the proposed model consistently outperforms the baseline VAR results from the reference paper for all six codecs. The reductions in MAE and RMSE values indicate a better model fit and stability. Lower MAPE values confirm improved forecasting accuracy for QoS parameters. This improvement mainly comes from three key updates in the proposed approach: Refined lag-order selection uses AIC, BIC, and HQIC to capture temporal dependencies more accurately. Better preprocessing techniques, such as

normalization and handling negative or missing values, improve the stability of model inputs. Noise control methods, including differencing and clipping, result in cleaner residual estimation and reduce unrealistic fluctuations. These updates lead to smoother, more realistic forecasts that closely match observed VoIP traffic behavior. The proposed pipeline not only replicated the original research findings but also expanded on. This shows the importance of careful statistical design and preprocessing in real-world forecasting tasks.

7.8. IMPROVED VAR FORECASTING STRUCTURE

The complete end-to-end Vector Autoregressive (VAR) forecasting framework was built in Java and included several important statistical modules. This integrated design allowed for automatic preprocessing, model fitting, and performance evaluation in one workflow, ensuring a stronger and more reliable forecasting process.

7.9. ENHANCED PREPROCESSING AND EVALUATION

These steps were crucial for addressing irregularities often found in raw VoIP datasets, like negative delay or bandwidth values. The cleaned and standardized data provided a more consistent foundation for training, leading to more stable parameter estimation and better predictive accuracy in model evaluation.

7.10. COMPARATIVE MODEL ANALYSIS

To explore linear and nonlinear dependencies in the dataset, the proposed framework compared the improved VAR model with two machine learning models: RF and XGBoost. The comparison used key performance indicators MAE, RMSE, and MAPE to ensure a fair assessment of model accuracy and robustness. The results showed that while the improved VAR model excelled in interpretability and short-term linear forecasting, the RF and XGBoost models better captured nonlinear and volatile patterns in the data. This evaluation highlights the complementary strengths of statistical and ensemble learning methods in modeling VoIP traffic behavior.

7.11. BASELINE-TO-PERFORMANCE IMPROVEMENT

The refined VAR implementation showed consistently higher accuracy and lower forecasting errors compared to the original reference model, especially for G.722 and G.729 codecs. These codecs often exhibit variable bandwidth and SNR characteristics, benefiting significantly from the hybrid evaluation and improved lag-selection strategy. The findings confirm that combining strict statistical criteria with careful preprocessing leads to major improvements in both forecast stability and realism.

7.12. PRACTICAL RELEVANCE

The improved forecasting models developed in this study have strong potential for real-time use in next-generation network monitoring systems. By adopting these models, network operators can actively manage resources, predict congestion, and ensure consistent QoS delivery in dynamic VoIP environments. Additionally, the forecasting framework can serve

as a foundation for adaptive network control systems, supporting smarter and more proactive management of mobile communication infrastructure.

CONCLUSION

This study looked at forecasting Voice over IP (VoIP) Quality of Service (QoS) parameters using real network traffic data. The proposed method used three predictive models: Vector Autoregressive (VAR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). It analyzed and predicted key QoS metrics such as MOS, Bandwidth, Jitter, RTT, Delay Jitter Buffer, and SNR. Among them, the improved VAR pipeline produced results that closely matched real measurements and had lower error rates than the baseline model from previous work. Using multiple lag selection criteria (AIC, BIC, HQIC) and more robust preprocessing steps improved the model's performance and robustness. The Random Forest and XGBoost models captured nonlinear relationships in the data. This complemented the VAR model's ability to handle time-related patterns. Together, these models create a flexible framework for forecasting VoIP traffic. This can support network resource management and optimize QoS in real-time settings. In the future, there are several ways to expand this work. First, hybrid models that combine deep learning methods, such as LSTM or CNN-LSTM networks, with VARs could better capture long-term time dependencies. Second, adaptive lag selection and dynamic parameter tuning could be added to boost performance under changing network conditions. Finally, implementing the forecasting framework in a real-time network monitoring system would enable continuous learning from live traffic. This would further improve its predictive ability and practical use.

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Conflict of Interest

The authors declare no conflict of interest.

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