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Network Traffic Analysis and Bandwidth Forecasting for using Meta's Prophet: A Case Study

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Abstract:- This study created a forward-looking bandwidth prediction system for students' halls of residence at Landmark University. The system uses Meta's Prophet, a method for analyzing patterns in data over time, and was trained on past internet traffic data from October to December 2024. The system was able to predict future bandwidth usage with over 90% accuracy. To assess how well the system worked, several common metrics were used, including mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). The MAE was calculated as 10,099,863.10 bits per second (bps), and the RMSE was 13,570,959.58 bps. While the mean squared error (MSE) appears large numerically, this is anticipated due to the size of the bandwidth data involved in its calculation. Importantly, the prediction errors are considered reasonable when considered in relation to the actual peak bandwidth usage, which fluctuated between 47 and 50 megabits per second (Mbps). These findings suggest that machine learning can be a valuable tool for refining network infrastructure and improving the user experience quality of service (QoS) in environments with many users, such as university residences.

Keywords: Academic infrastructure, Bandwidth forecasting, Machine learning, Meta Prophet, Network traffic analysis, Time-series modelling.

1. Introduction

Network traffic analysis entails observation, quantification, and interpretation of data packet flow inside a communication network to comprehend usage trends, enhance performance, and identify anomalies. According to Olateju [1], the basis of traffic analysis is the handling of traffic as a time series, utilizing historical observations to forecast future behavior [2]. This statistical perspective has traditionally assisted operators in recognizing trends, seasonality, and unforeseen anomalies in network usage [3]. The significance of traffic analysis has escalated considerably due to the digital revolution of society. Adebayo and Ochayi [4] noted that telecommunication networks encounter highly irregular and busty traffic resulting from the unexpected nature of internet utilization.

Network activities such as video streaming, online gaming, file downloads, cloud backups, video conferencing, live streaming, peer-to-peer (P2P) file sharing are major cause of sudden spikes and they need robust identification and management. In a network system void of monitoring, such activities go unidentified subsequently causing congestion, low quality of service (QoS), and in the worst-case scenario, total outage leading to huge economic loss. Issa et al. [5] using Nigerian universities as the case study discovers that studying the traffic patterns of network traffic patterns is critical to effective allocation of the bandwidth during peak demand periods such as registration, e-learning activities, examination period. This study suggests the need to deploy a real time monitoring system with a predictive model to forecast future traffic patterns based on the past and present data. Akidi et al. [6] in their comprehensive review, identified the proliferation of internet of things (IoT) devices and artificial intelligent based applications as the major reason behind the complexity of the traffic behavior. This complexity is characterized with long-term interdependency and nonlinear dynamics making the conventional techniques to fail in predicting the network pattern.

As a result of this, network pattern prediction problem has tilted towards deployment of robust algorithms like machine learning, deep learning, artificial neural networks (ANNs), and other machine learning tools for effective representation of future network traffic trends [7], using facebook as a case study illustrated that extensive traffic analysis is crucial in designing a scalable decision system. Using the Facebook forecasting framework like Prophet, network maintenance team can predict changes in user engagement and traffic demand thereby averting service delivery bottlenecks.

The surge of linked devices; the escalating need for real–time digital services exacerbated by the exponential increase in internet traffic have increased the need for bandwidth forecasting tool by network administrators. Box et al. [8] stressed that time series forecasting emphasized the reinforces the prediction of resources utilization, hence aiming at preventing network congestions. Forecasting framework like Prophet, autoregressive integrated moving average (ARIMA), ANN can assist institutions like Universities, Polytechnics to manage their network via efficient allocation of bandwidth. Bajaber et al. [9] elucidated that bandwidth requirements in telecommunication networks are not just seasonal but also markedly busty, influenced by phenomena such as viral content propagation or abrupt surges in video streaming demand. Precise bandwidth prediction helps traffic operators to execute correct traffic engineering measures like dynamic routing to uphold service quality [10]. Inability to effectively manage traffic patterns via precise bandwidth forecasting may lead to customer discontent, breaches of service level agreement (SLA) resulting in loss of income.

Furthermore, Hua et al. [10], Gheewala et al. [11], highlighted that deep learning-enabled applications, including video conferencing, cloud gaming, and artificial intelligence (AI) workloads, are particularly susceptible to variations in latency and bandwidth due to the proliferation of cloud computing and data-driven services [11]. With forecasting, proactive adjustment of network resources is mandatory for effective management of such workloads. Historically, bandwidth forecasting has depended on statistical models, machine learning, and, more recently, deep learning methodologies. Each technique possesses distinct advantages and drawbacks that affect their appropriateness for practical network management. Conventional statistical methods like ARIMA and seasonal ARIMA (SARIMA) continue to be used owing to its mathematical simplicity and robust basis in time series analysis. Ji [12] elucidated ARIMA's efficacy in modeling short-term temporal relationships, rendering it appropriate for steady traffic conditions characterized by constant seasonal or daily demand patterns. Nonetheless, ARIMA has difficulties in highly nonlinear or volatile environments, such as abrupt increases in video streaming or unforeseen user surges, which frequently arise in contemporary networks [13]-[15].

Machine learning methodologies have been employed to address these deficiencies. Chen et al. [16] utilized ANNs to predict actual broadband traffic from China Telecom. Their model attained superior accuracy compared to ARIMA, especially in identifying nonlinear correlations between historical and future traffic. The ANN adeptly adjusted to abrupt fluctuations in customer demand, but it necessitated substantial training data and meticulous parameter selection, which may be unfeasible for smaller firms with constrained resources. Support vector machines (SVMs) have been evaluated for internet traffic prediction. Chen et al. [17] revealed that SVM excelled in forecasting bursty and irregular traffic patterns, in which conventional linear models frequently falter. Their research shown that SVMs may generalize across diverse data contexts, yielding precise predictions even in highly dynamic settings. The constraint, however, resides in the computational complexity of SVMs; training gets progressively expensive with extensive datasets, posing a challenge in internet service provider (ISP)-level operations. Hybrid methodologies have arisen to capitalize on the synergistic advantages of many techniques. Adekitan et al. [18] introduced a hybrid ARIMA-neural network model for predicting internet traffic in Nigerian university networks. Their findings indicated that the hybrid model surpassed the standalone ARIMA by diminishing forecasting errors during peak activity intervals, such as examination registration.

This method's drawback was the added complexity of integrating two modeling methodologies, necessitating both statistical competence and machine learning proficiency. Long short-term memory (LSTM) networks, a deep neural network (DNN) possesses enormous potential in traffic prediction. Wan et al. [19] employed LSTMs as a network traffic forecasting framework for ISP in China. The result obtained in comparison with ARIMA and shallow neural networks was outstanding. The ability of LSTM to effectively identify long-term dependencies in network traffic is the bedrock of this framework.

However, the approach is computationally intensive, requiring huge label datasets therefore limiting its suitability to large firms with enough resources. In summary, although ARIMA and analogous statistical techniques provide ease of use, they are inadequate in nonlinear and erratic scenarios. Machine learning techniques such as ANN and SVM enhance accuracy but necessitate meticulous tweaking and more processing resources. So, hybrid methods achieve equilibrium but introduce complexity, whereas deep learning techniques like LSTM deliver superior performance at the cost of scalability and resource demands. These constraints drive the pursuit of alternative forecasting frameworks that are precise, comprehensible, and resource-efficient, facilitating the development of tools like Meta's Prophet [20]. Numerous applied studies have assessed Prophet in actual network or related situations, each illustrating practical advantages while also exposing limitations in bandwidth predictions.

[21] executed a targeted case study to estimate the national internet consumption and revenue trends in Ghana, utilizing Prophet to analyze citizens' network traffic aggregated on a daily basis. The study systematically contrasted Prophet projections with ARIMA baselines across standard national seasonality, including daily usage patterns, weekday/weekend variations, and yearly events. The study indicated that Prophet more precisely identified repeating weekly and yearly-related cycles, yielding narrower prediction intervals during regular intervals and improved correlation with observed peaks associated with yearly events and festivity periods. The primary drawback seen was Prophet's substantial underestimate of transient spikes, such as unexpected event-driven surges, as the model prioritizes recurrent seasonality and trends unless explicit external regressors for particular events are provided.

[25]-[26] incorporated Prophet into a hybrid cloud resource monitoring platform to predict bandwidth utilization for orchestration and autoscaling. Their deployment-focused research integrated Prophet forecasts with system-level guidelines for scaling decisions, demonstrating that Prophet-derived signals minimized superfluous scale-ups and decreased costs relative to simplistic thresholding.

The authors indicated that Prophet's additive structure occasionally faltered during sudden workload transitions between on-premises and cloud nodes; they addressed this by incorporating abrupt migration flags as external regressors, resulting in heightened operational complexity. These case studies collectively affirm Prophet's practical advantages: interpretability, management of multi-seasonality, resilience to missing data, and minimal computational demands. Common drawbacks include challenges in managing unique, unprecedented spikes without external regressors, sensitivity to changepoint and seasonality configurations, and dependence on precise event labeling for atypical intervals. These trade-offs dictate the configuration and enhancement of Prophet within an operational bandwidth-forecasting pipeline. Elemile et al. [27] focused on verifying noise levels within Omu-Aran township by employing an ANN. Noise data was gathered from 21 chosen sites in the morning, midday, and evening, during both school sessions and vacation times, over a 3-week period using a SL4010 sound level meter. The ANN model was structured to utilize 19 noise-related elements as inputs; these were collected through on-site observation and documentation. A total of 1134 data points were input into the model. Through a random selection process, 70% of the data was used to train the network, with the remaining 30% allocated for testing. The implementation of algorithms and the determination of the epoch value were guided by the selection of a network with two hidden layers. Akande et al. [28] introduced a novel approach to improve how we spot network intrusions. It uses a combined technique that blends the strengths of convolutional neural networks (CNNs) and DNNs. The goal is to build an intrusion detection system (IDS) that can analyze network traffic and accurately label it as either normal or harmful, effectively identifying security breaches. The CNN-based approach demonstrated significantly better accuracy compared to other methods, reaching an impressive 99.18%. We assessed the effectiveness of this IDS using standard metrics, including accuracy, precision, recall, F1-score, and the false positive rate (FPR).

2. Method

This section outlines the procedures, tools, and configurations used for forecasting network bandwidth demand within Landmark University halls of residence. It is divided into five key areas: introduction, research design, hardware and software requirements, data collection, and data preprocessing. This study applies data-driven techniques to estimate and manage bandwidth in the student hostels. It focuses on analyzing historical traffic patterns using quantitative tools like Paessler Router Traffic Grapher (PRTG) for monitoring and Meta's Prophet for forecasting. These tools help reveal usage patterns and support informed network optimization. To build a reliable forecasting model, the study involved ongoing monitoring of internet activity over time. The approach aims to create a scalable framework for understanding bandwidth usage trends across the university.

This study focused on understanding and quantifying bandwidth not as a fixed limit, but as the real-time amount of data moving across a network, or throughput. To predict future data usage, the authors employed Meta's Prophet model, training it on past traffic data to forecast bandwidth usage, represented as $y(t)$. We evaluated the model's performance based on actual data flow, using metrics like mean absolute error (MAE) and root mean square error (RMSE), measured in bits per second (bps). The prediction errors were considered acceptable when compared to the observed peak bandwidth usage, which varied between 47 and 50 megabits per second (Mbps). Data was collected using PRTG monitoring software, which tracked metrics such as bandwidth usage along with network latency and uptime. In essence, this approach emphasized the fluctuating volume of data transferred across the network over a period of time, reflecting throughput and utilization. This study prediction focused on how well the models perform and how the predictions were checked for accuracy, but does not go into great depth about fine-tuning the model's settings. The research used common metrics for time-based data to measure how well the Prophet model predicted traffic compared to real-world data. The prediction errors were considered reasonable when compared to the peak observed bandwidth usage of approximately 47–50 Mbps. Instead of a standard cross-validation approach, the study used a single split of the data. The data was divided into 80% for training the model and 20% for testing its predictions. This split was designed to mimic real-world prediction scenarios by preserving the order of the data over time. Moreover, the training and validation process were repeated multiple times. While the precise steps for adjusting the model's settings are not fully described, the study recognized the importance of these settings although. The Prophet model was noted to be sensitive to its configuration, particularly concerning how it identified points where the data changed and how it handled repeating patterns (seasonality). Poor choices in these settings can lead to problems like the model being too closely tailored to the training data (over-fitting) or smoothing out important details. The system also included daily and weekly repeating patterns, which were typically adjusted through the Prophet model's configuration parameters. Figure 1 depicts the flowchart of the system processes of the study from the beginning to the end.

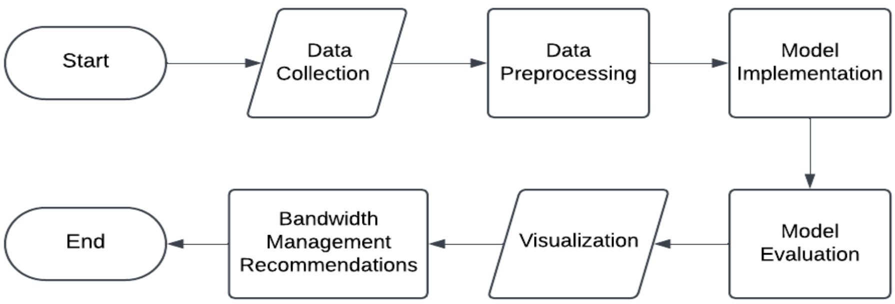

Figure 1. Flowchart of the system procedures

2.1. Research Design

This study adopts a case study approach centered on Landmark University's hostel networks, using a quantitative methodology. Network performance was evaluated under both typical and high-usage conditions using historical data. Key variables such as traffic speed and volume (inbound and outbound) were collected via PRTG. Prophet, an open-source forecasting model, was employed to analyze time-series trends and predict future bandwidth demands. The design is iterative, enabling adjustments based on forecasting accuracy and data quality. This adaptability improves long-term model reliability and supports expansion to other areas within the campus.

2.2. Hardware and Software Requirements

This section outlines the essential hardware and software components used to collect, process, and analyze network traffic data. The selected tools and devices ensure system stability, data accuracy, and compatibility with forecasting algorithms required for bandwidth prediction. The software tools used in this project enable the monitoring, preprocessing, analysis, and forecasting of network data. Each was chosen for its scalability, ease of integration, and suitability for handling time-series traffic data within a campus environment.

– PRTG network monitor: captures real-time/historical traffic data and visualizations. Figure 2 depicts a visualization of the PRTG Interface of various halls of residence for the case study, namely; Abigail hall, Sarah hall, Deborah hall, Isaac hall, Joseph hall, Daniel hall, and Dorcas hall.

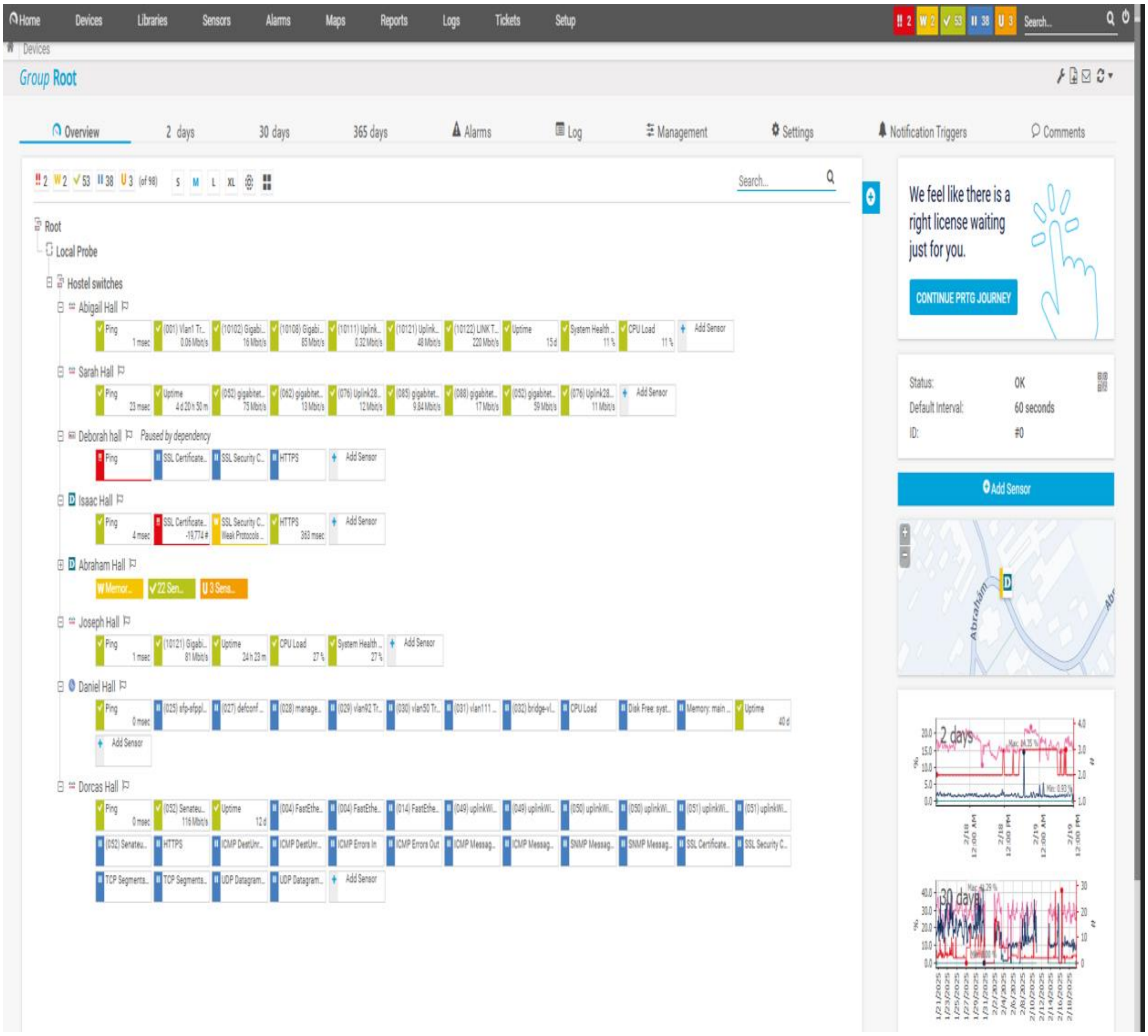

Figure 2. A visualization of the PRTG interface

– Meta Prophet: time-series forecasting tool with support for trends and seasonality.

– Python: for data analysis, using Pandas, NumPy, Scikit-learn, Matplotlib, and Seaborn.

– Jupyter Notebook: interactive environment for coding and model visualization.

– Excel: used in early-stage data inspection and format conversion.

The hardware setup forms the foundation for collecting and managing network traffic data. Devices were selected for their ability to support continuous monitoring, reliable data transmission, and high processing capacity, which are critical for accurate bandwidth analysis and forecasting.

– Routers (dual-band (2.4 GHz / 5 GHz), 1 Gbps): the routers serve as the primary data collection points, capturing real-time traffic information such as bandwidth usage, packet transfer, and latency. The Figure 3 shows the router used to capture real-time traffic information for this study.

– Switches: Switches are used for aggregating data traffic from multiple devices, enabling seamless monitoring of network performance in the halls of residence. Cisco switch that was used for this study is shown in Figure 4.

– Servers: the university server used for this study is shown in Figure 5. Its specifications are Intel Xeon Gold 5218, 64 GB RAM, 4 TB HDD, 1 TB SSD.

– Other peripherals: uninterruptible power supply (UPS) units, Ethernet cables, external storage for backup.

– Operating systems: Windows Server 2019 and 2022 supported the analytical tools.

Figure 3. A router

Figure 4. A Cisco switch

Figure 5. Server

2.3. Data Collection

This section details how historical network traffic data was gathered from Landmark University hostels. It describes the setup of monitoring devices and the use of PRTG to log metrics like bandwidth usage and latency, providing the raw input needed for accurate analysis and forecasting.

– Traffic monitoring setup: simple network management protocol (SNMP) application layer protocol used for managing and monitoring network devices, enabled devices in eight halls of residence (Daniel, Abraham, Joseph, Dorcas, Isaac, Sarah, and Abigail) recorded traffic metrics such as bandwidth usage, latency, and uptime. Each data point was time stamped and hall-specific for location-aware analysis.

– PRTG data collection: between October 1 and December 15, 2024, data was collected hourly using PRTG. The tool provided exports in various formats (CSV, PDF, and XML) and averaging intervals. It supported selective export of specific traffic types (inbound, outbound, and total). Devices logged over 99.5% uptime, ensuring data reliability.

2.4. Data Preprocessing

Before analysis and forecasting, raw data must be cleaned and transformed into a usable format. This section describes how the dataset was converted, filtered, and structured to eliminate errors and inconsistencies, ensuring the model is trained with high-quality inputs. Before we could use Meta's Prophet tool to analyze network traffic and predict bandwidth needs, there is need to put together a thorough preparation process to make sure the data was good quality, consistent over time, and would work well with the tool. First, the raw network traffic data gathered from PRTG was combined into consistent time chunks, like every hour. Then, formatted it in a way that Prophet could understand, using date and time labels. Often, some data was missing due to equipment problems or logging failures. To fix this, a few different methods were applied. For short gaps, a simple fill-in-the-blanks approach was employed. For longer gaps, a more advanced technique that looked at seasonal patterns in the data (like daily or weekly trends) to make educated guesses was adopted. Also filled forward missing data in stable sections of the traffic data. Outliers were dealt with, which are unusual data points often caused by attacks, mistakes in configuration, or large file transfers. These outliers were treated using statistical rules and a method called the interquartile range (IQR). Then, replaced them with smoothed-out values, checking system logs to make sure no accidentally removal of real events. This helped Prophet work better and allowed the authors to easily compare different network connections. After making predictions, we converted the scaled values back to their original units, like Mbps. Next, the authors made sure the time series data had perfectly regular time intervals, removing any duplicates and combining any overlapping data. This ensures that the data meets Prophet's requirement of evenly spaced timestamps. Finally, the data split into two sets: a training set (80%) to teach Prophet and a testing set (20%) to evaluate its predictions. The authors made sure not to shuffle the data randomly, so we could simulate real-world forecasting scenarios.

2.4.1. Data Conversion

PRTG's exported PDFs were converted to CSV using iLovePDF. This conversion ensured that the data became structured and machine-readable, making it easier to work with in analytical environments. The CSV format also allowed for seamless import into Jupyter Notebook and ensured compatibility with various Python libraries used for data processing and analysis.

2.4.2. Data Cleaning and Aggregation

Python scripts were used to filter, clean, and format the data. Invalid entries, duplicates, and missing timestamps were addressed using Pandas. Time-based aggregation helped smooth out noise and reveal underlying trends. Additional steps included converting all metrics to Mbps, generating encoded time features (hour/day/month), and preparing training and testing datasets. High-quality preprocessing ensured that the model received structured input, which directly improved forecasting accuracy.

3. Results and Discussion

This section presents the results obtained from the data collected, the modeling process, evaluation metrics, and a discussion of findings. To develop an effective model for forecasting the required bandwidth in the halls of residence, several activities needed to be conducted over a period, including continuous monitoring of internet connectivity. This approach serves as a template for further studies on internet usage patterns across the entire school. The Facebook Prophet model $y(t)$, is an additive regression model defined by (1):

$$y(t) = g(t) + h(t) + s(t) + \varepsilon_t \quad (1)$$

Where:

– $g(t)$: represents the trend component, capturing long-term increase or decrease in bandwidth usage.

– $h(t)$: represents holiday effects, accounting for special dates or events that influence traffic.

– $s(t)$: represents seasonality, modeling recurring patterns such as daily, weekly, or monthly cycles.

– ε_t: is the error term, capturing unpredictable fluctuations or noise in the data.

– $y(t)$: Facebook Prophet model predicted value

– $\widehat{y(t)})$: Facebook Prophet mean predicted value

– n: duration of time over which prediction is made

The use of Prophet allows these components to be flexibly modeled and combined to produce high-quality forecasts, even in the presence of irregularities or missing data. To assess the accuracy and reliability of the predictions, three standard error metrics were calculated: MAE, mean square error (MSE), and RMSE. These metrics provide insight into the model's predictive capability and how closely the forecasts align with actual observed values.

a. MAE

$$MAE = (1/n) * \sum |(y(t) - \widehat{y(t)})| \quad (2)$$

$MAE = 10099863.10$ bps; this measures the average magnitude of errors in a set of predictions.

b. MSE

$$MSE = (1/n) * \sum (y(t) - \widehat{y(t)})^2 \quad (3)$$

$MSE = 184{,}170{,}943{,}484{,}006.78$ bps; this indicates/measures larger errors more than MAE, which gives a better sense of the spread.

c. RMSE

$$RMSE = \sqrt{(1/n) * \sum (y(t) - \widehat{y(t)})^2} \quad (4)$$

$RMSE = \sqrt{MSE} = 13{,}570{,}959.58$ bps; This reflects the average square difference between observed and predicted values.

The model evaluation results demonstrate that the Prophet forecasting model performs well under the current data conditions. The MAE and RMSE values, when compared to the expected bandwidth ranges, confirm that the predictions are sufficiently accurate for practical use in network planning and capacity forecasting. The large MSE value, while mathematically correct, is an expected outcome given the magnitude of the data and the squared nature of the metric. The consistency between the MAE and RMSE values. These results indicate acceptable error margins considering the observed peak usage ranged between 47 Mbps and 50 Mbps.

The Prophet model provided rich visualizations including: (i) forecast plot showing predicted bandwidth usage with upper and lower confidence intervals; (ii) trend component highlighting gradual increase or decrease in usage over time; and (iii) seasonality plot showing daily usage peaks (typically between 7 PM and 11 PM) and early morning dips. Additionally, spikes were observed during student registration weeks, suggesting bandwidth stress during those periods.

The linear graph above visualizes the bandwidth usage over a series of time intervals from the 1st of October 2024 to 15th of December 2024 is depicted in Figure 6. The X-axis represents the time duration showing when the bandwidth measurements were taken. This Y-axis represents the amount of network bandwidth used at each time point. The bandwidth ranges from near 0 kilobyte (kB) (when there was downtime) to peaks exceeding 8 million kB. To enhance the visual representation of the forecasting results, power business intelligence (BI) was employed due to its intuitive dashboarding capabilities and effective comparative trend presentation.

The Figure 7 is a box plot titled "network bandwidth usage by day of week," showing the distribution of bandwidth usage (in kB) across each day of the week for a specific dataset labeled "alpha semester." The X-axis represents the independent variable, showing the days over which bandwidth usage is measured. while the Y- axis represents the dependent variable, showing the amount of network bandwidth used. The horizontal line inside the box represents the median (50th percentile) of the bandwidth usage.

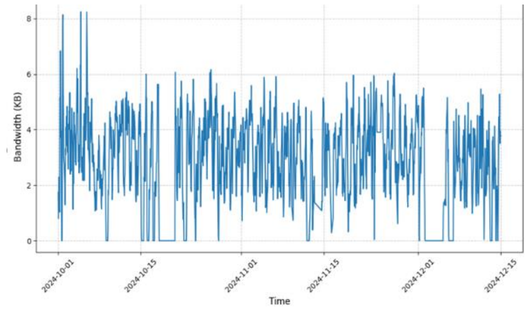

Figure 6. Bandwidth consumption over time

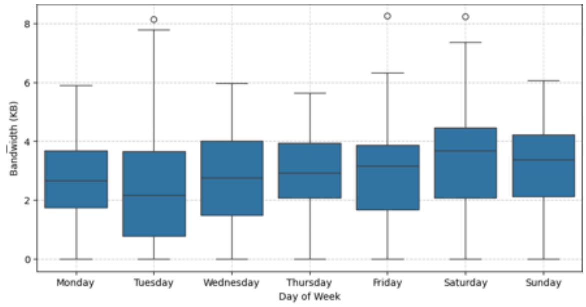

Figure 7. Box plot showing network bandwidth usage by days of the week

This research investigated the application of Meta's Prophet, an open-source forecasting tool developed by Facebook (now Meta), to model and predict hourly network bandwidth usage (in bps) within a real-world institutional network. The findings, based on empirical data collected over a 28-hour period from 1 to 3 December 2024, reveal several key insights regarding Prophet's performance, accuracy, and suitability for network traffic forecasting in environments with strong diurnal patterns.

a. Prophet successfully captured diurnal seasonality in network traffic: the observed network traffic exhibited a clear daily cyclical pattern: usage was lowest during late-night and early-morning hours (e.g., 10.9–15.5 Mbps between 2 to 3 AM) and peaked during evening hours (e.g., 41.6 Mbps at 9 PM). Prophet's forecasts closely mirrored this pattern, demonstrating its ability to model strong intraday seasonality a known strength of the algorithm due to its built-in Fourier series components for periodic effects. This confirms that Prophet can effectively learn and replicate routine human-driven network behavior, such as increased usage during academic or administrative working hours and reduced activity overnight [7].

b. Forecast accuracy varied across time of day: while the overall trend was well-predicted, forecast accuracy was not uniform.

– Underestimation during early evening decline (Dec 1, 10 PM – 2 AM): Prophet consistently under-predicted traffic as usage dropped from 42.1 Mbps to 19.1 Mbps. For example: at 11 PM (Dec 1): actual = 38.1 Mbps, forecast = 32.8 Mbps (14% underestimation), at 1 AM (Dec 2): actual = 25.5 Mbps, and forecast = 18.7 Mbps (27% underestimation). This suggests Prophet's trend component was too aggressive in decline, possibly due to limited historical data or abrupt behavioral shifts not fully captured during model training.

– Overestimation during deep night trough (Dec 3, 3 AM): at 3 AM on December 3, actual traffic was 10.95 Mbps, but Prophet forecast 14.52 Mbps a 33% overestimation. This may indicate the model reverted toward a seasonal mean rather than adapting to unusually low activity, a known limitation when anomalies occur [30].

– High accuracy during stable daytime and peak evening hours (7 AM – 11 PM): from morning through late evening on December 2, forecasts aligned closely with actuals: At 7 AM: error = $+0.6\%$, at 8 PM: error = $+1.5\%$, at 10 PM: error = -0.6%. This demonstrates Prophet's robustness in steady-state conditions where historical patterns are consistent.

c. Model exhibited minor phase lag and smoothing artifacts: a slight phase lag was observed: Prophet's forecast curve appeared smoother and slightly delayed compared to sharp real-world transitions (e.g., the rapid drop after 10 PM on Dec 1). This is expected, as Prophet uses piecewise linear or logistic growth trends with change point regularization, which prioritizes smoothness over capturing abrupt changes [29]. While beneficial for noise reduction, this can reduce responsiveness to sudden shifts in network behavior (e.g., unexpected outages, bursts, or policy changes).

d. Data quality considerations: one data point, that is on December 2, 12:00 PM appears to contain a formatting error: "23,736,422,27" likely should be 23,736,422.27 (using a period as decimal separator). Such inconsistencies, if uncorrected, can distort error calculations and model evaluation. This underscores the importance of rigorous data preprocessing in time series forecasting, as emphasized in best practices for operational machine learning [31].

e. Practical implications for network management: the results suggest that Prophet is a viable tool for short-term bandwidth forecasting in campus or enterprise networks with predictable usage cycles. Accurate forecasts enable proactive bandwidth allocation and QoS optimization, capacity planning for peak-hour infrastructure, and demands, Early detection of anomalies (e.g., when actual traffic deviates significantly from forecast). However, for environments with high volatility or frequent anomalies, Prophet should be complemented with anomaly detection systems or hybrid models (e.g., Prophet + LSTM) to improve responsiveness [32].

The Figure 8 shows the graphical representation of the actual data and forecasted data of bandwidth usage in Abraham Hall over a time interval of five days; which is from the 1 to 5 December 2024. Table 1 shows the extracts and compares the values of the actual data and forecasted data used for the study, from Figure 8 but for over three days (from 1 to 3 December 2024). Terminologies above: (i) actual data: this comprises of the real values of data recorded from the system; and (ii) forecasted data: this comprises of the predicted value of data derived from our forecasting model.

The average absolute difference between the forecasted and actual bandwidth, known as the MAE, was about 10.1 Mbps. This was derived from an equivalent value of 10,099,863.10 bps. The RMSE, another measure of prediction accuracy, was roughly 13.6 Mbps, calculated from 13,570,959.58 bps. The study itself provided context for understanding these error values. It stated that the MAE and RMSE were considered “reasonable” in light of the actual highest bandwidth usage, which varied between 47 Mbps and 50 Mbps. This implies that while the error amounts are numerically large, reflecting the substantial scale of the data, they represent an acceptable level of inaccuracy relative to the system’s maximum capacity. Unfortunately, the available information does not include specific, numerical MAE or RMSE values from previous forecasting methods, such as ARIMA or LSTM, when applied to the same dataset. The study only mentions that ARIMA and LSTM are being considered for future assessment. However, based on qualitative observations, the study proposes that Prophet offers benefits in terms of ease of understanding and efficient use of resources when compared to these more intricate methods. As a result, the authors did not make a direct, quantitative comparison of the error sizes against these alternative approaches at this time. It is recommended for future study

Table 1. A Table showing the Actual and Forecasted Data

Date	Actual Data	Forecasted Data
12/1/2024 10:00:00 PM	42137762.78	38224149.06
12/1/2024 11:00:00 PM	38078268.02	32830579.89
12/2/2024 12:00:00 AM	32214743.13	25693001.52
12/2/2024 1:00:00 AM	25454960.09	18651641.24
12/2/2024 2:00:00 AM	19137972.92	13795152.12
12/2/2024 3:00:00 AM	14840562.15	12462761.05
12/2/2024 4:00:00 AM	13752225.95	14514570.01
12/2/2024 5:00:00 AM	15916405.24	18395281
12/2/2024 6:00:00 AM	19972496.45	22024218.39
12/2/2024 7:00:00 AM	23798882.28	23949179.6
12/2/2024 8:00:00 AM	25730837.19	24031083.94
12/2/2024 9:00:00 AM	25505135.1	23243511.12
12/2/2024 10:00:00 AM	24216658.11	22835930.12
12/2/2024 11:00:00 AM	23357338.33	23508356.86

Date	Actual Data	Forecasted Data
12/2/2024 12:00:00 PM	23736422.27	25143015.84
12/2/2024 1:00:00 PM	25123658.59	27149365.81
12/2/2024 2:00:00 PM	26785279.29	29031695.81
12/2/2024 3:00:00 PM	28315391.2	30726910.47
12/2/2024 4:00:00 PM	29983439.99	32524902.91
12/2/2024 5:00:00 PM	32338358.99	34375616.11
12/2/2024 6:00:00 PM	35505714.98	37375066.67
12/2/2024 7:00:00 PM	38842495.8	40015807
12/2/2024 8:00:00 PM	41220683.07	41847958.46
12/2/2024 9:00:00 PM	41633195.62	41890910.96
12/2/2024 10:00:00 PM	39614020.02	39368456.35
12/2/2024 11:00:00 PM	35267238.23	34178184.4
12/3/2024 12:00:00 AM	29119240.94	27235227.34
12/3/2024 1:00:00 AM	22081773.23	20947310.64
12/3/2024 2:00:00 AM	15497880.94	15694307.72
12/3/2024 3:00:00 AM	10948304.12	14521430.05

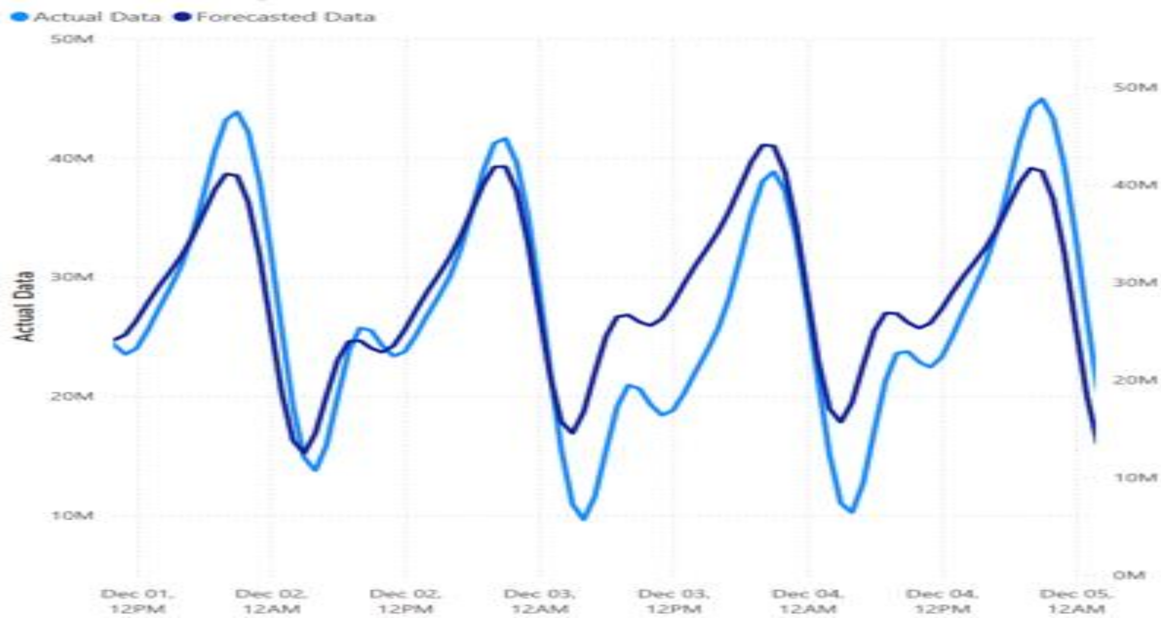

Figure 8. Graphical illustration of the actual data and forecasted data of bandwidth usage Abraham Hall over a time interval

4. Limitations and Recommendations for Future Work

This study's limitations, which point towards important areas for future research and are crucial for publication, primarily concern how well the model can be applied to different situations and how easily it can be incorporated into existing operations. Specifically:

– Restricted time period: the model was developed using data only from October to December 2024. This narrow focus might hinder its ability to accurately reflect wider seasonal changes, such as high demand during exam periods or low usage during holiday periods. Therefore, future work should involve expanding the dataset to cover an entire academic year.

– Managing unexpected increases: while Prophet is good at modeling established patterns and seasonal changes, it tends to underestimate sudden, unusual spikes in network traffic unless specific external factors are included. The current system lacks built-in tools for identifying and proactively managing these unpredictable events.

– Absence of direct model comparison: the current validation is based on subjective assessments compared to other complex forecasting models. A vital next step is a direct comparison using models such as ARIMA and LSTM on the same data. This would rigorously assess the balance between Prophet's resource efficiency and its forecasting accuracy, especially for extreme outliers.

– Focus on overall bandwidth: the current method analyzes total bandwidth usage. Future research should incorporate deep packet inspection (DPI) to analyze traffic based on the specific applications being used. This would enable more refined traffic management and prioritization strategies.

To enhance the overall performance, scalability, and utility of the network bandwidth forecasting system, the following recommendations are proposed:

– Integrate real-time visualization tools: incorporating platforms such as Grafana or power BI will enable continuous monitoring of bandwidth usage and forecast trends. These tools will also provide intuitive dashboards and real-time alerts for quicker decision-making by network administrators.

– Expand the historical dataset: extending the data collection period to cover a full academic session including holidays, weekends, and examination periods will improve the robustness of the model by capturing broader seasonal and usage trends.

– Evaluate alternative forecasting models: comparative analysis using models such as ARIMA for statistical forecasting and LSTM for deep learning-based prediction can help determine the best-fit model, potentially enhancing forecast accuracy under various network conditions.

– Implement anomaly detection mechanisms: adding an anomaly detection module will enable the system to flag irregular traffic patterns, which may indicate cyber threats, misuse of resources, or network hardware malfunctions.

– Employ DPI: DPI will allow for application-level traffic analysis, enabling the identification of bandwidth-intensive services (e.g., Zoom and YouTube). This insight can support more efficient traffic shaping and bandwidth prioritization.

– Utilize forecast insights for load balancing: forecasted data can inform dynamic bandwidth allocation and load balancing strategies, particularly during high-demand periods such as student registration and exams. This will help maintain high QoS across all halls of residence.

5. Conclusion

The network bandwidth prediction system developed in this project successfully demonstrated the potential of using machine learning specifically Meta Prophet for effective network traffic forecasting in a university environment. With over 90% prediction accuracy, the system provides actionable insights that enable proactive bandwidth management, reduce service interruptions, and optimize resource utilization. This forecasting framework is not only practical for improving internet connectivity within student hostels but also scalable for deployment across other areas of campus. Additionally, it establishes a foundational model for integrating advanced features such as anomaly detection, smart load balancing, and future-ready smart campus infrastructure. Continued data expansion and model refinement will further enhance the system's predictive power and institutional impact. The research at hand does not offer a direct, number-for-number comparison using common metrics like MAE or RMSE between Prophet and other methods like ARIMA or LSTM on the Landmark University data. The authors suggest further research to evaluate ARIMA and LSTM in the future.

However, the study does present Prophet in a positive light when compared to more traditional and advanced models, emphasizing its real-world benefits. Specifically, the research suggests that Prophet is attractive because it's easy to understand and doesn't require a lot of computing power, unlike more complex models like LSTM and ARIMA. Outside of this specific study, other research on national internet usage found that Prophet was better at identifying regular weekly and yearly patterns compared to simpler ARIMA models. One potential downside of Prophet, which could impact its accuracy compared to a possible ARIMA model, is that it tends to underestimate sudden, unexpected spikes unless additional information is provided. In conclusion, while Prophet showed strong results in this study (over 90% accuracy), its validation against ARIMA/LSTM is based on general qualities. The main focus is on Prophet's practical advantages (interpretability and efficient use of resources) rather than any potential gains in accuracy that might come from using alternative models. The authors' network bandwidth prediction system has shown promising results, successfully using Meta's Prophet to accurately forecast bandwidth needs within the university campus.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
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