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Internet Bandwidth Forecasting by Using Fuzzy Time Series in Zainal Abidin General Hospital, Indonesia

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Abstract

Data bandwidth capacity is a critical component of internet infrastructure management, directly impacting network efficiency and operational costs. Accurate measurement and forecasting of bandwidth requirements are essential to optimize resource allocation. This study utilizes a Fuzzy Time Series (FTS) approach for bandwidth forecasting, leveraging its ability to capture complex patterns from historical data without requiring the rigid statistical assumptions of classical forecasting methods. A forecasting model was developed and implemented to predict data bandwidth requirements at the Zainal Abidin General Hospital (RSUZA). Utilizing historical data collected from February 1, 2019, to April 29, 2019, the model's performance was evaluated using the Mean Absolute Percentage Error (MAPE). The proposed method achieved a MAPE of 6.45%, demonstrating high accuracy and falling into the "highly accurate" category.

1. Introduction

The internet has become an inseparable component of modern society, seamlessly integrated into daily human activities [1]. Today, digital connectivity is ubiquitous and readily accessible. The paradigm shift toward digitalization is evident in the surging reliance on e-commerce platforms for electronic transactions and the widespread use of social media and emails for global communication. However, delivering an optimal and seamless internet experience heavily relies on maximizing and managing data bandwidth capacity.

Bandwidth is defined as the maximum transfer rate or data transmission capacity between computers over a Local Area Network (LAN) or the internet [2]. Strategic calculation of bandwidth is imperative to guarantee network stability while meeting user demands. Accurate capacity planning is crucial for optimizing network efficiency and cost-effectiveness [3]. Allocating excessive bandwidth leads to financial inefficiency and resource waste, whereas under-provisioning results in severe network degradation and poor quality of service. Therefore, measuring and forecasting bandwidth requirements stands as a critical phase in network management. In this context, bandwidth demand represents the aggregate volume of bandwidth utilized by a specific group of network users within a given timeframe and under certain operational requirements [4].

Forecasting bandwidth demand significantly enhances the Quality of Service (QoS) and assists organizations in optimizing operational expenditure for bandwidth leasing [5]. Network provisioning must strictly align with actual requirements; over-provisioning causes costly bandwidth underutilization, while under-provisioning triggers latency, directly disrupting user experience. Furthermore, shared internet architectures are highly sensitive to performance drops as the concurrent user base expands. Consequently, network performance plays a pivotal role in regulating bandwidth distribution across diverse web applications and services.

However, the parameters used to forecast bandwidth capacity often exhibit high degrees of uncertainty and ambiguity. For instance, peak traffic loads frequently present fluctuations that cannot be characterized by precise numerical levels. To address these ambiguous parameters, fuzzy logic offers a robust framework for decision-making through fuzzy rules [6]. The primary advantage of fuzzy methods lies in their superior ranking and decision-making capabilities, which effectively select optimal alternatives from a given set based on a tolerance for imprecise data. Moreover, fuzzy logic is highly capable of modeling complex non-linear functions, making it a more versatile and efficient methodology compared to alternative classical techniques [7].

Among the various soft computing methods, Fuzzy Time Series (FTS) stands out as a prominent forecasting tool selected for this study. Compared to conventional intelligent methods such as Genetic Algorithms (GA) or Artificial Neural Networks (ANN), FTS does not require the rigid statistical assumptions or complex training phases typically inherent in classical models [8]. Historically, FTS has been successfully deployed in diverse forecasting domains, such as predicting student enrollment at the University of Alabama, utilizing fuzzy set theory, fuzzy logic, and approximate reasoning [9]. FTS forecasting effectively captures historical data patterns to project future trends [10]. By extracting patterns from historical network logs, an FTS-based forecasting system can reliably project future bandwidth demands without the computational burden of complex learning mechanisms. Consequently, this makes the proposed forecasting model highly scalable and straightforward to develop.

Nevertheless, extensive research has been dedicated to developing forecasting models for internet bandwidth utilization using various conventional approaches. For instance, Zhou et al. [11] utilized the Autoregressive Integrated Moving Average (ARIMA) model to predict institutional network traffic, while Tipu et al. [12] implemented Artificial Neural Networks (ANN) to capture complex bandwidth patterns. Additionally, Dudek [13] explored linear regression techniques for short-term capacity planning, and Shakila and Shaik [14] applied the Holt-Winters exponential smoothing method to handle seasonal network demands. Despite their contributions, these existing studies exhibit significant limitations. Conventional statistical models like ARIMA and linear regression heavily rely on strict assumptions, such as data linearity and normality, which are rarely met in highly volatile network environments. On the other hand, intelligent methods like ANN, while powerful, suffer from high computational complexity, require extensive training datasets, and often act as "black boxes" that lack interpretability. These constraints create a critical research gap in developing a forecasting model that is computationally efficient, free from rigid statistical assumptions, and capable of handling imprecise or uncertain data patterns. Consequently, this study bridges this gap by deploying the FTS approach, offering a more flexible, reliable, and accessible alternative for forecasting dynamic web bandwidth demands.

Despite significant advancements in network management, existing bandwidth forecasting methods often fall short in handling the highly volatile, non-linear, and uncertain nature of modern network traffic. Traditional statistical models typically rely on strict assumptions of data stationarity, making them insufficient for capturing sudden traffic spikes or complex patterns.

To address the abovementioned limitations and critical research gaps, this study proposes an FTS approach. Unlike conventional methods, FTS inherently excels at modeling high uncertainty and linguistic vagueness without requiring complex statistical assumptions. By leveraging FTS, this research effectively captures the non-linear dynamics of bandwidth data, thereby providing a more robust, adaptive, and accurate forecasting solution that overcomes the limitations of current frameworks. This study provides two primary contributions to the field of network management and predictive analytics. First, it designs and develops a model tailored for forecasting data bandwidth requirements, utilizing the robust FTS framework. Second, this study rigorously analyzes the accuracy and performance of the FTS method in predicting dynamic bandwidth demands, evaluated through standard statistical metrics. By validating the precision of this soft computing approach, the research offers valuable empirical insights into optimizing network

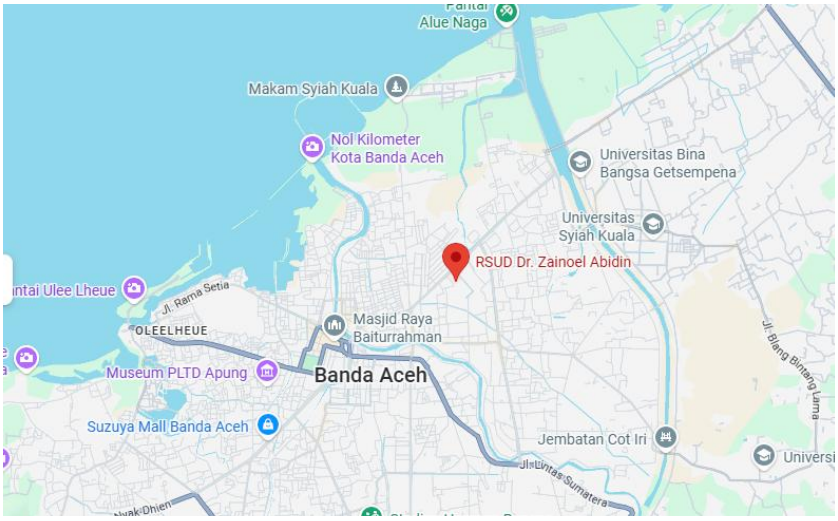

Figure 1. The hospital location generated by Google Maps.

efficiency, preventing resource underutilization, and minimizing operational costs in institutional networks.

The remainder of this paper is systematically organized into four distinct sections. Section 2 delineates the materials and methods, detailing the system architecture, data collection process, and the algorithmic implementation of the proposed forecasting application. Section 3 presents the experimental results, performance evaluations, and a comprehensive analysis of the forecasting accuracy. Finally, Section 4 concludes the paper by summarizing the core findings and outlining potential directions for future research.

2. Materials and Methods

2.1. Dataset and Location

The primary dataset utilized in this study consists of network bandwidth consumption data, measured in Gigabits per second (Gbps). The data was retrieved from the central server of the Zainal Abidin General Hospital (RSUZA), Indonesia using CACTI, a robust network monitoring and graphing tool. The temporal scope of the dataset spans from February 1, 2019, to April 29, 2019. To ensure relevance to peak institutional operations, the data collection specifically targets working days, precisely monitoring bandwidth traffic from Monday to Friday.

The empirical dataset utilized in this study comprises a total of 56 observations, captured at a daily frequency over the specified temporal range. To evaluate the forecasting performance of the proposed FTS model robustly, the dataset was partitioned into a training set and a testing set using an 80:20 split ratio. Specifically, the training phase utilized 45 observations to construct and optimize the fuzzy logical relationships. Meanwhile, the remaining 11 observations were reserved strictly as an independent testing set to validate the model's predictive accuracy.

The study was conducted at the Zainal Abidin General Hospital (RSUZA), a major regional healthcare facility. The hospital is located at Tgk. Daud Beureueh Street No. 108, Banda Aceh, Aceh, Indonesia. Geographically, the site is situated at the coordinate points of approximately 5° 33' 39'' N latitude and 95° 20' 11'' E longitude. The spatial orientation and precise layout of the study site, along with its corresponding geographical map, are illustrated in Figure 1.

2.2. Architecture of the Proposed Fuzzy Time Series (FTS) Model

To effectively capture the highly dynamic and non-linear patterns of network traffic, this study introduces a tailored FTS architecture designed specifically for Internet bandwidth forecasting. The systematic workflow and structural components of the proposed FTS model are illustrated in Figure 2.

The architectural framework of the proposed FTS model for Internet bandwidth forecasting is systematically structured into two core phases: the Training and Modeling Phase, and the Operational Forecasting Phase. This framework is designed to capture the highly dynamic, non-linear, and stochastic nature of network traffic by transforming raw numerical bandwidth data into meaningful linguistic patterns. By establishing a robust rule-based transition mechanism, the architecture ensures accurate multi-step or single-step ahead projections without relying on rigid traditional statistical assumptions. Figure 2 illustrates the detailed logical workflow and structural components of the proposed FTS architecture.

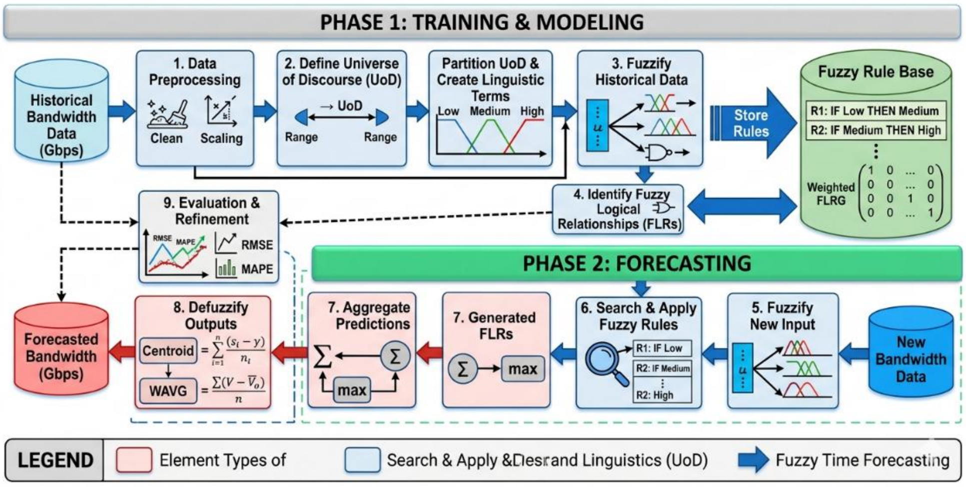

Figure 2. The proposed FTS architecture for internet bandwidth forecasting.

The architecture initiates with the Training and Modeling Phase, which establishes the foundation of the predictive model using historical network traffic logs. The first critical step is Data Preprocessing, where raw internet bandwidth data undergo rigorous cleaning, noise filtering, and standardization to eliminate anomalies and transmission outliers. The raw bandwidth consumption data underwent a rigorous three-step preprocessing pipeline prior to the fuzzification process. First, data cleaning was performed to handle missing timestamps through Seasonal Mean Imputation [15]. Second, to eliminate high-frequency anomalies and transient traffic spikes that could distort the forecasting model, a noise filtering operation was executed using a Median Filter [16], which effectively smoothed the time-series baseline without shifting critical temporal patterns. This comprehensive preprocessing pipeline ensures that the FTS model can capture the underlying data patterns effectively without being biased by extreme outliers or scale discrepancies.

Following preprocessing, the framework defines the Universe of Discourse (*U*) based on the minimum and maximum boundaries of the historical dataset, which is subsequently segmented during the Partitioning of Fuzzy Sets. In this stage, the continuous range of bandwidth consumption is divided into distinct, overlapping intervals. Each interval corresponds to a specific linguistic value—such as low, moderate, or peak traffic—and is mapped utilizing mathematical membership functions to ensure a smooth transition between different network states.

Once the universe of discourse is partitioned, the historical data are translated from a numerical domain into a linguistic domain through the Fuzzification of Historical Data. Each crisp bandwidth record is assigned a degree of membership within the defined fuzzy sets, effectively converting precise numbers into granular fuzzy values. These sequential fuzzy values are then analyzed chronologically to achieve the Identification of Transition Rules (FLRs). By examining how network traffic shifts from one state to another over successive time intervals, the system constructs a comprehensive Fuzzy Logical Relationship (FLR) matrix. This matrix functions as the core knowledge base of the architecture, capturing recurring temporal patterns, daily cyclical trends, and sudden bandwidth surges inherent in network infrastructures.

The operational deployment of the model is executed within the Forecasting Phase, which utilizes the established rule base to predict future bandwidth demands in real time. When new, live bandwidth metrics are fed into the system, they immediately undergo the Fuzzification of New Input, mapping the current real-world network state into its corresponding linguistic representation. This fuzzified input is subsequently passed to the Application of Fuzzy Rules engine. The engine queries the previously generated knowledge base to identify matching transition rules, determining the most probable future fuzzy states based on the historical behavior of identical or similar network conditions.

To produce an actionable and practical output for network administrators, the inferred fuzzy states must be converted back into a deterministic format through the Defuzzification process. This step translates the combined linguistic predictions into a single, crisp numerical value representing the forecasted internet bandwidth capacity. Finally, the entire architecture is governed by an ongoing Evaluation and Refinement loop. By continuously evaluating the defuzzified outputs against actual real-time traffic statistics using standard performance metrics—such as Mean Absolute Percentage Error (MAPE) [17]—the system provides iterative feedback. This feedback loop allows for the dynamic adjustment of partition boundaries and transition weights, thereby ensuring sustained high accuracy and adaptability to evolving network traffic trends.

MAPE is a measure of prediction accuracy for a forecasting method in statistics. MAPE is calculated by dividing the absolute error in each period by the actual observed value for that period. Next, the average value of these absolute percentage errors is calculated. This approach is useful when the size or magnitude of the forecast variable differences is used to evaluate forecast accuracy. MAPE indicates how large the forecast error is compared to the actual values. Calculating the MAPE between the actual data and the forecasting results is done using Equation (1) where x_t is the actual data value at period t, $F(t)$ is the forecasted value at period t, and n is the total number of time periods or the amount of data.

$$MAPE = \frac{1}{n}\left(\sum_{t=1}^{n}\left|\frac{x_t - F(t)}{x_t}\right| \times 100\%\right) \qquad (1)$$

According to Lewis [18], the accuracy criteria of MAPE are divided into four categories. These criteria are highly accurate, good, reasonable, and inaccurate. A prediction's accuracy is considered highly accurate when its MAPE value is less than 10%, categorized as good when the MAPE value is between 10% and 20%, considered reasonable when the MAPE value is between 20% and 30%, while the forecasting is deemed inaccurate when the MAPE value is greater than 30%.

In addition, to avoid unbiased evaluation of the FTS model, the reported forecasting performance measures, specifically the MAPE, were calculated strictly during the out-of-sample testing phase. The experimental framework utilized a robust train-test split mechanism, where the historical time-series data was divided sequentially. The model's parameters and fuzzy logical relationships were established solely using the in-sample training dataset. Subsequently, the independent out-of-sample testing dataset, consisting of unseen data points completely isolated from the training phase, was employed to generate the final forecasts. Evaluating the model via this out-of-sample approach guarantees that the resulting MAPE accurately reflects the model’s generalization capacity and actual predictive performance on future real-world data, effectively ruling out the risk of data leakage or overfitting.

In the model evaluation process, the comparative performance analysis in this study evaluated the forecasting results of the proposed FTS model against several baseline models, specifically the AutoRegressive Integrated Moving Average (ARIMA) [19], Regressive Integrated Moving Average (RIMA/ARMA) [19], Simple Exponential Smoothing (SES) [20], and Simple Moving Average (SMA) [21], based on their MAPE values. The parameters for these baseline frameworks were systematically determined using standardized statistical criteria. For the ARIMA(p, d, q) and ARMA(p, d, q) models, the optimal lag orders were identified through Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, and subsequently finalized by selecting the configuration that minimized the Akaike Information Criterion (AIC). The values of p, d, and q for the ARIMA model was empirically set to 1, 1, and 1, respectively, whereas for the ARMA model was set to 1, 0, and 1, respectively. Regarding the SES model, the smoothing constant (α) was obtained through an automated grid-search optimization restricted to the range of [0, 1], selecting the specific value that minimized the training phase's Mean Squared Error (MSE). Lastly, the window size (*k*) for the SMA model was empirically set to $k = 3$, aligning with the weekly cyclic patterns observed in the bandwidth traffic. This systematic parameterization guarantees that each baseline model operates at peak performance, providing a robust foundation for the MAPE-based comparative evaluation.

2.3. The Computational Procedures of FTS Algorithm

Fuzzy Time Series (FTS) is a forecasting method rooted in the principles of fuzzy logic. Unlike conventional forecasting methods, an FTS-based framework captures underlying patterns from historical data to project future values without requiring strict statistical assumptions, such as stationarity or normality [22]. FTS was pioneered by Song and Chissom [23] and has since been extensively adapted by researchers to resolve complex forecasting problems across various domains [24].

The fundamental distinction between FTS and conventional time series lies in the nature of the data values used during the forecasting process. While conventional methods rely strictly on crisp real numbers, FTS utilizes fuzzy sets derived from a defined universe of discourse. A fuzzy set can be understood as a class of objects with unsharp or vague boundaries, where membership is defined by a continuum of grades.

In FTS, the relationships between chronological data points are governed by fuzzy logical relationships or transition rules. The formal mathematical definition of FTS, as established by Song and Chissom [23], is outlined below:

Let $Y(t)(t = 1,2,3, \dots)$ be the universe of discourse by which fuzzy sets $f_i(y)$ are defined. If $F(t)$ is a collection of $f_1(t)$, $f_2(t)$, $f_3(t)$, …, then $F(t)$ is defined as a fuzzy time series on $Y(t)$. From this definition, $F(t)$ can be regarded as a linguistic variable, whereas $f_i(t)$ represents the possible linguistic values of $F(t)$. It is important to note that $F(t)$ is a function of time t; hence, the values of $f_i(t)$ can vary across different time intervals depending on the dynamic nature of the universe of discourse. Furthermore, if the current state of $F(t)$ is caused strictly by its immediate predecessor $F(t-1)$, the fuzzy logical relationship is denoted as: $F(t-1) \rightarrow F(t)$.

A critical challenge in traditional FTS models lies in their reliance on fixed and subjective interval lengths, which often leads to a loss of critical data patterns [25]. This limitation is highly evident in the foundational FTS model developed by Song and Chissom [23], where static partitioning fails to accommodate complex data behaviors [25]. To overcome this weakness, the FTS variant developed by Chou [26] introduces a more dynamic and adaptive framework by utilizing an optimized approach to determine interval lengths based on empirical data distribution. Unlike the static partitioning found in the formulations of Song and Chissom, Chou's method effectively minimizes human bias during fuzzification, captures non-linear fluctuations more precisely, and significantly reduces forecasting errors. Consequently, this variant provides superior methodological rigor and robustness, making it particularly effective for handling highly volatile datasets [26].

According to Chou [26], there are five steps to perform forecasting using the FTS method. These steps are as follows:

Step 1. Defining the Universe of Discourse and Intervals.

The universe of discourse $U = [D_L, D_U]$ can be defined such that shown in Equation (2):

$$U = \begin{cases} D_L = D_{min} - \dfrac{s\, t_{\alpha(n)}}{\sqrt{n}}, and\ D_U = D_{max} - \dfrac{s\, t_{\alpha(n)}}{\sqrt{n}} n \leq 30 \\ D_L = D_{min} - \dfrac{s\, Z_{\alpha(n)}}{\sqrt{n}}, and\ D_U = D_{max} - \dfrac{s\, Z_{\alpha(n)}}{\sqrt{n}} n > 30 \end{cases} \tag{2}$$

where $D_L$is the minimum value of linguistic term, $D_U$is the maximum value of linguistic term, $D_{min}$is the minimum value of the actual dataset, $D_{max}$is the maximum value of the actual dataset, s, σ is the standard deviation value, *n* is the number of data, and $t_\alpha(n), Z_\alpha(n) = 100(1-\alpha)$is a value of *t*-distribution with *n* degrees of freedom.

Step 2. Defining Fuzzy Sets and Fuzzifying Historical Data

Assume that the linguistic values of the data are extremely slow, very slow, slow, moderate, fast, very fast, and extremely fast. Thus, U_1 = 'extremely slow', U_2 = 'very slow', U_3 = 'slow', U_4 = 'moderate', U_5 = 'fast', U_6 = 'very fast', and U_7 = 'extremely fast'. To ensure a precise mapping of the crisp historical data into fuzzy sets, the fuzzification process begins by establishing the universe of discourse, $U = [D_L, D_U]$, which is partitioned into a finite number of intervals, $U_i = Supp(U_i)$. The interval boundaries (U_i) are systematically determined by utilizing Chou's heuristic optimization method, which adjusts the length of each interval based on the density and distribution of the empirical data points, rather than using equal fixed lengths, and also called the support value of the linguistic terms. The support value of these linguistic values can be defined using Equation (3):

$$Supp(U_i) = \begin{cases} \left[D_{min} + \dfrac{(i-1)(D_U - D_L)}{m}, D_{max} + \dfrac{i(D_U - D_L)}{m}\right] 1 \leq i \leq m-1 \\ \left[D_{min} + \dfrac{(i-1)(D_U - D_L)}{m}, D_L + \dfrac{i(D_U - D_L)}{m}\right] i = m \end{cases} \tag{3}$$

where *m* is a number of interval and $Supp(U_i)$ is support value of U_i.

Step 3. Establishing Fuzzy Logical Relationships (FLRs)

The FTS is given by $F(t) = U_i$, where $d(t) = Supp(U_i)$ and $d(t)$ are the actual data with respect to time t.

Step 4. Determining Rules of FTS

The determination of this transition rule begins from the time period $t-1$ to t and is denoted as $F(t-1) \rightarrow F(t)$. Then, aggregate all time periods of the transition rule. Create the rule based on that rule to match Equation (4):

$$R = \{r_i | r_i : U_i \rightarrow U_i\} \tag{4}$$

Step 5. Calculating and Predicting Forecasted Values

The value of $T(t)$ can be predicted by FTS using the created transition rule from Equation (4). Assume $T(t) = \{r_i | d(t) \in Supp(U_i)\}$ where $r_i \in R$ is the rule set with respect to $d(t)$, where $Supp(U_i)$ is the support value of U_i. Assume $\bar{S}upp(U_i)$ is the median of $Supp(U_i)$, then the predicted value for $d(t)$ can be determined through Equation (5):

$$forecast(d(t)) = \frac{1}{|T(t-1)|} \sum_{r_i \in T(t-1)} \bar{S}upp(U_i) \tag{5}$$

where $|T(t-1)|$is the cardinality or the number of elements of the set $T(t-1)$.

3. Results and Discussion

3.1. An Application of FTS for Internet Bandwidth Forecasting

This section presents the step-by-step implementation of the FTS model proposed by Chou [26] to forecast internet

Table 1. Fuzzifications of a sample of the raw bandwidth.

Date (*t*)	**Bandwidth (d(t))**	**Fuzzification (F(t))**
February 1, 2019	28091	U_6
February 4, 2019	27890	U_5
February 5, 2019	26754	U_5
February 6, 2019	25434	U_4
February 7, 2019	29308	U_6
February 8, 2019	27338	U_5
February 11, 2019	29558	U_6
…	…	…
April 29, 2019	23498	U_3

Table 2. Transition rules from period *t* to *t*-1.

Time Period	**Transition Rules**
F (February 1, 2019) → *F* (February 4, 2019)	$U_6 \to U_5$
F (February 4, 2019) → *F* (February 5, 2019)	$U_5 \to U_5$
F (February 5, 2019) → *F* (February 6, 2019)	$U_5 \to U_4$
F (February 6, 2019) → *F* (February 7, 2019)	$U_4 \to U_6$
F (February 7, 2019) → *F* (February 8, 2019)	$U_6 \to U_5$
F (February 8, 2019) → *F* (February 11, 2019)	$U_5 \to U_6$
F (February 11, 2019) → *F* (February 12, 2019)	$U_6 \to U_6$
…	…
F (April 28, 2019) → *F* (April 29, 2019)	$U_3 \to U_3$

bandwidth consumption. The historical bandwidth utilization data is processed through a structured algorithmic sequence to capture nonlinear patterns and generate accurate future predictions. Step-by-step implementation of the FTS algorithm is the following:

Step 1. Defining the Universe of Discourse and Intervals.

The first step requires determining the universe of discourse, $U = \left[D\left(\frac{\sigma\cdot t_\alpha(n)}{\sqrt{n}}\right)\left(\frac{\sigma\cdot t_\alpha(n)}{\sqrt{n}}\right)_{max_{min}}\right]$, based on the minimum ($D_{min}$) and maximum ($D_{max}$) values found in the historical bandwidth dataset where σ is a standard deviation value and $t_\alpha(n) = 100(1-\alpha)$ is a value of *t*-distribution with *n* degrees of freedom. For instance, if the minimum bandwidth recorded is 19276 Gbps, the maximum is 30166 Gbps, the standard deviation is 2123.32, a forecasting confidence level is 99.5% ($t_\alpha = 0.005$), and the number of data is $n = 62$such that the corresponding normal distribution table value is $t(n) = 2.65747$, the universe of discourse can be defined as *U* = [18559, 30883]. Following Chou's framework, this universe is partitioned into seven equal-length intervals, $U_1, U_2, U_3, \dots, U_7$, where $Supp(U_1) = [19276{,}21037]$, $Supp(U_2) = [21037{,}22797]$, $Supp(U_3) = [22797{,}24558]$, $Supp(U_4) = [24558{,}26318]$, $Supp(U_5) = [26318, 28079]$, $Supp(U_6) = [28079{,}29839]$, and $Supp(U_7) = [29839{,}30166]$.

Step 2. Defining Fuzzy Sets and Fuzzifying Historical Data

Next, linguistic variables (fuzzy sets) $U_1, U_2, U_3, \dots, U_n$ are defined on the universe of discourse U. The membership functions are established based on the intervals determined in Step 1. Each historical bandwidth observation is then mapped into its corresponding fuzzy logical value. Based on the formed linguistic values, the fuzzy set for each bandwidth data can be determined. For example, the fuzzification process for the actual data at time t = (February 8, 2019), t = (February 11, 2019), and t = (February 6, 2019) are as follows:

$$\begin{aligned} F(t) &= U_i, \text{ where } \quad d(t) \in \quad Supp(U_i) \\ F(\text{February } 8, 2019) &= U_i, \text{ where } 27338 \in \quad Supp(U_5) \\ &= U_5, \text{ where } 27338 \in [26318{,}28079] \end{aligned}$$

$$\begin{aligned} F(t) &= U_i, \text{ where } \quad d(t) \in \quad Supp(U_i) \\ F(\text{February } 11, 2019) &= U_i, \text{ where } 29558 \in \quad Supp(U_6) \\ &= U_6, \text{ where } 29558 \in [28079{,}29839] \end{aligned}$$

$$\begin{aligned} F(t) &= U_i, \text{ where } \quad d(t) \in \quad Supp(U_i) \\ F(\text{February } 6, 2019) &= U_i, \text{ where } 25434 \in \quad Supp(U_4) \\ &= U_4, \text{ where } 25434 \in [24558{,}26318] \end{aligned}$$

Table 1 illustrates a sample of the raw bandwidth data alongside its fuzzified representations.

Step 3. Establishing Fuzzy Logical Relationships (FLRs)

To capture the chronological transitions in bandwidth utilization, Fuzzy Logical Relationships (FLRs) are constructed. An FLR is expressed as $U_i \to U_j$, where U_i represents the bandwidth state at time $t-1$ (current state) and U_j represents the state at time *t* (next state). Based on Table 1, the transitions are established as Table 2.

Table 3. Transition rules from period *t* to *t*-1.

No.	Rules of Fuzzy Time Series	No	Rules of Fuzzy Time Series	No	Rules of Fuzzy Time Series
1	$\{ r_1 : U_1 \to U_4 \}$	9	$\{ r_9 : U_4 \to U_7 \}$	17	$\{ r_{17} : U_5 \to U_1 \}$
2	$\{ r_2 : U_2 \to U_5 \}$	10	$\{ r_{10} : U_4 \to U_5 \}$	18	$\{ r_{18} : U_6 \to U_5 \}$
3	$\{ r_3 : U_3 \to U_2 \}$	11	$\{ r_{11} : U_4 \to U_3 \}$	19	$\{ r_{19} : U_6 \to U_6 \}$
4	$\{ r_4 : U_3 \to U_5 \}$	12	$\{ r_{12} : U_5 \to U_5 \}$	20	$\{ r_{20} : U_6 \to U_7 \}$
5	$\{ r_5 : U_3 \to U_6 \}$	13	$\{ r_{13} : U_5 \to U_4 \}$	21	$\{ r_{21} : U_6 \to U_4 \}$
6	$\{ r_6 : U_3 \to U_4 \}$	14	$\{ r_{14} : U_5 \to U_6 \}$	22	$\{ r_{22} : U_7 \to U_5 \}$
7	$\{ r_7 : U_3 \to U_3 \}$	15	$\{ r_{15} : U_5 \to U_3 \}$	23	$\{ r_{23} : U_7 \to U_3 \}$
8	$\{ r_8 : U_4 \to U_6 \}$	16	$\{ r_{16} : U_5 \to U_7 \}$	24	$\{ r_{24} : U_7 \to U_6 \}$

Step 4. Determining Rules of FTS

Based on Table 2, the fuzzy time series rules can be formed by eliminating identical and repeated transition rules. The formation of fuzzy time series rules using Equation (4) and the result can be seen in Table 3.

Step 5. Calculating and Predicting Forecasted Values

The final process is the forecasting and defuzzification process based on the formed fuzzy time series rules. All median values of the support value $Supp(U_i)$ are calculated beforehand to perform the defuzzification process; the calculation results of $\bar{S}upp(U_i)$ are as follows: $\bar{S}upp(U_1) = 20156.5$, $\bar{S}upp(U_2) = 21917$, $\bar{S}upp(U_3) = 23677.5$, $\bar{S}upp(U_4) = 25438$, $\bar{S}upp(U_5) = 27198.5$, $\bar{S}upp(U_6) = 28959$, and $\bar{S}upp(U_7) = 30002.5$,

After the median value of $Supp(U_i)$ is calculated, assign the cardinality value of $|T(t-1)|$ to each data time period; the results of assigning the transition values to several bandwidth data of $T('August2{,}2019')$ and $T('November2{,}2019')$ are as follows:

$$\begin{aligned} T(August\ 2, 2019) &= \{r_i | d(August\ 2, 2019) \in Supp(U_5), r_i \in R\} \\ &= \{r_{12}, r_{13}, r_{14}, r_{15}, r_{16}, r_{17}\} \\ &= \{U_5 \otimes U_5, U_5 \otimes U_4, U_5 \otimes U_6, U_5 \otimes U_3, U_5 \otimes U_7, U_5 \otimes U_1\} \end{aligned}$$

$$\begin{aligned} T(November\ 2, 2019) &= \{r_i | d(November\ 2, 2019) \in Supp(U_6), r_i \in R\} \\ &= \{r_{18}, r_{19}, r_{20}, r_{21}\} \\ &= \{U_6 \otimes U_5, U_6 \otimes U_6, U_6 \otimes U_7, U_6 \otimes U_4\} \end{aligned}$$

Therefore, the predicted values for $forecast('August2{,}2019')$ and $forecast('November2{,}2019')$ are:

$$\begin{aligned} forecast('\,August\ 2, 2019\,') &= \frac{1}{|T(t-1)|} \sum_{r_i \in T(t-1)} \bar{S}upp(U_i) \\ &= \frac{1}{|\{r_{12}, r_{13}, r_{14}, r_{15}, r_{16}, r_{17}\}|} \sum_{r_i \in T(t-1)} \begin{pmatrix} \bar{S}upp(U_5) + \bar{S}upp(U_4) + \bar{S}upp(U_6) + \\ \bar{S}upp(U_3) + \bar{S}upp(U_7) + \bar{S}upp(U_1) \end{pmatrix} \\ &= \tfrac{1}{6}(27198.5 + 25438 + 28959 + 23677.5 + 20156.5) \\ &= 25905.33 \end{aligned}$$

$$\begin{aligned} forecast('\,November\ 2, 2019\,') &= \frac{1}{|T(t-1)|} \sum_{r_i \in T(t-1)} \bar{S}upp(U_i) \\ &= \frac{1}{|\{r_{18}, r_{19}, r_{20}, r_{21}\}|} \sum_{r_i \in T(t-1)} \left(\bar{S}upp(U_5) + \bar{S}upp(U_6) + \bar{S}upp(U_7) + \bar{S}upp(U_4)\right) \\ &= \tfrac{1}{4}(27198.5 + 28959 + 30002.5 + 25438) \\ &= 27899.5 \end{aligned}$$

The prediction results for forecasting the data bandwidth requirements of Zainal Abidin General Hospital can be seen in Appendix A.

3.2. Discussion and Performance Evaluation

To comprehensively evaluate the efficacy of the proposed FTS model in forecasting internet bandwidth requirements, a rigorous comparative analysis was conducted against four alternative forecasting methodologies. The benchmark techniques include the ARIMA, RIMA/ARMA, SES, and SMA. Performance evaluation was quantified utilizing the MAPE metric calculated on a row-by-row basis across the entire historical dataset. This multi-model comparison serves to validate whether incorporating fuzzy logic principles

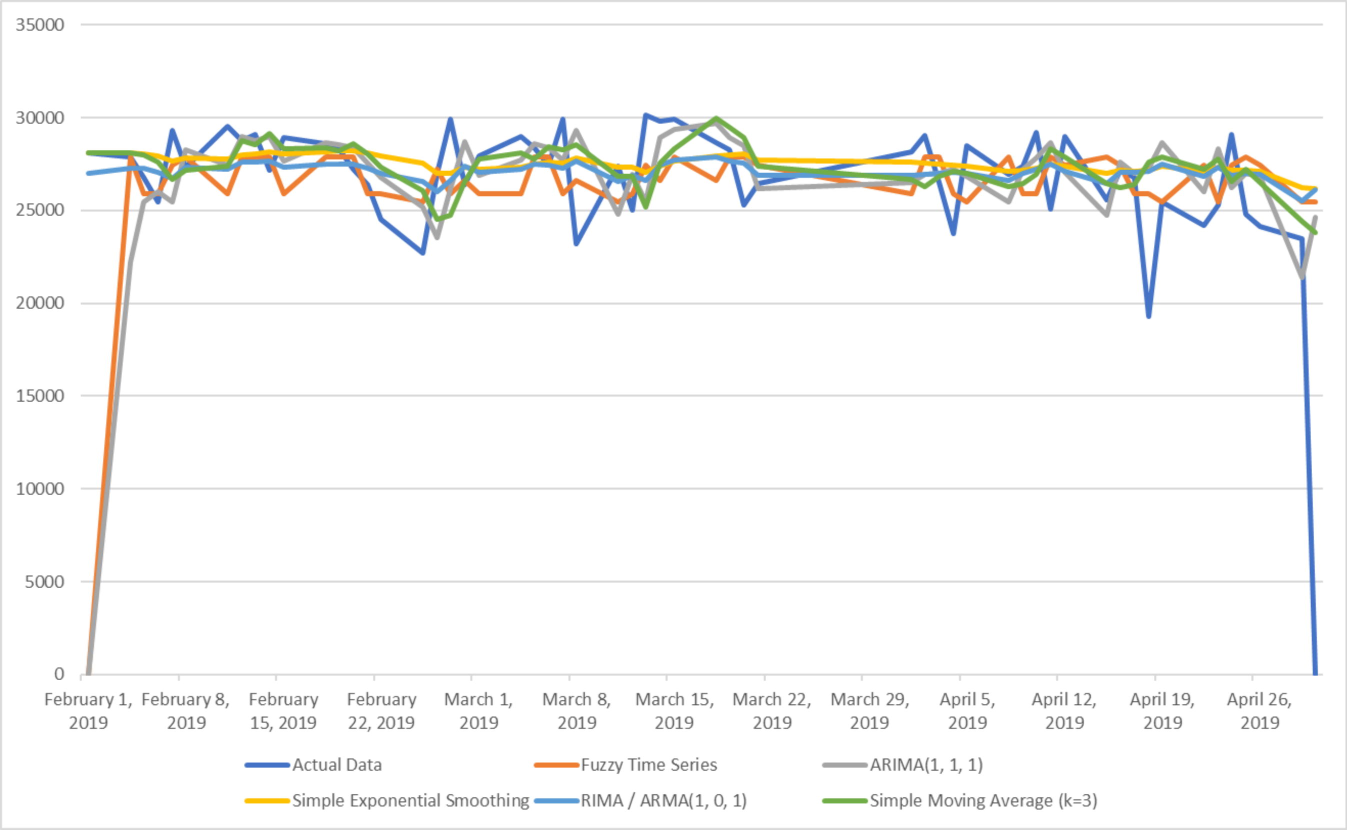

Figure 3. Comparison of performance evaluation across all methods.

offers measurable superior precision over classical statistical and smoothing time-series approaches. The performance evaluation across all methods can be seen in Figure 3.

The empirical results derived from the performance evaluation demonstrate that all five forecasting models exhibit high prediction accuracy, yet subtle disparities in error margins highlight the structural advantages of certain approaches. A forecasting model is deemed "highly accurate" if its final MAPE value falls below the 10% threshold. Notably, every single methodology evaluated in this study achieved a MAPE of less than 7%, thereby categorizing all of them as highly accurate models suitable for robust infrastructure planning. However, the exact precision rank reveals distinct characteristics among the models, with the proposed FTS model clearly outperforming the remaining statistical configurations.

The comparative analysis reveals that the FTS model yields the lowest overall error margin, achieving a remarkably precise final MAPE of 6.45%. This superior performance can be attributed to the inherent capability of FTS to effectively map daily non-linear fluctuations and navigate linguistic uncertainties within the bandwidth demand patterns without relying on strict parametric assumptions. In contrast, the classical ARIMA(1, 1, 1) model emerged as the second-best performer with a MAPE of 6.84%. While ARIMA successfully accounted for daily trend transitions through its integrated differencing component, it still exhibited a slightly higher deviation compared to the granular interval-based formulation of the fuzzy approach.

Furthermore, the models that did not incorporate trend-differencing mechanisms or complex historical weighting fell slightly further behind in accuracy. The RIMA/ARMA(1, 0, 1) model recorded a MAPE of 6.90%, followed closely by the SES model at 6.92%, which utilized an optimized smoothing constant (α). The Simple Moving Average (SMA) model with a three-day window ($k = 3$) generated the highest error margin among all candidates, concluding with a MAPE of 6.95%. The fact that SMA and SES produced higher errors indicates that simple historical averaging and exponential decay weights are somewhat less effective at capturing sudden spikes or drops in hospital network utilization compared to FTS and ARIMA. Consequently, these findings underscore that while traditional smoothing methods provide a baseline for highly accurate forecasting, the integration of fuzzy time series logic represents the optimal framework for achieving maximum precision in bandwidth capacity management. The comparative result can be seen in Table 4.

Table 4. Comparison of final MAPE values across all methods

Rank	Forecasting Methods	Final MAPE	Category
1	Fuzzy Time Series (FTS)	6.45%	Highly Accurate
2	ARIMA(1, 1, 1)	6.84%	Highly Accurate
3	RIMA / ARMA(1, 0, 1)	6.90%	Highly Accurate
4	Simple Exponential Smoothing (SES)	6.92%	Highly Accurate
5	Simple Moving Average (k=3)	6.95%	Highly Accurate

As presented in Table 4, the performance evaluation reveals that the FTS model achieved the lowest overall error, registering a MAPE of 6.45%, followed closely by ARIMA (6.84%), ARMA (6.90%), SES (6.92%) and SMA (6.95%). While the FTS variant demonstrates a marginal advantage in minimizing forecasting errors, the relatively narrow margin between these outcomes suggests that all evaluated baseline models possess a comparably high level of predictive accuracy for this specific dataset. Therefore, rather than implying absolute architectural superiority, these findings indicate that the FTS model serves as a highly competitive and robust alternative. It successfully captures non-linear traffic dynamics effectively, yielding optimized results while maintaining a performance standard consistent with established statistical frameworks.

The performance advantage of the FTS model over traditional statistical baselines can be attributed to its intrinsic capability to handle the unique characteristics of network bandwidth data. Bandwidth traffic inherently exhibits high volatility and non-linear fluctuations driven by dynamic user activities, which often manifest as sudden spikes or sharp drops. Traditional models like ARIMA, ARMA, SES, or SMA operate on strict assumptions of linearity and stationarity, making them less adaptable to such abrupt shifts. Conversely, the FTS framework excels in uncertainty handling because it does not rely on rigid numerical transitions; instead, it converts complex numerical data into meaningful intervals through linguistic partitioning. By mapping volatile data points into logical linguistic intervals, the model effectively dampens the disruptive effects of minor noise and traffic anomalies. This robust partitioning mechanism allows the FTS model to approximate non-linear trends with greater flexibility, thereby offering superior stability and a more reliable interpretation of network traffic behaviors.

4. Conclusions

This study has comprehensively evaluated and compared the performance of the FTS model against four conventional forecasting methodologies, including ARIMA, RIMA/ARMA, SES, and SMA, in predicting internet bandwidth requirements. Based on the empirical evaluation utilizing the final MAPE computed on a row-by-row basis, all examined models demonstrated high predictive accuracy, successfully falling below the 10% threshold to be classified as "highly accurate" according to Lewis's criteria. Notably, the proposed FTS model outperformed all statistical benchmarks, achieving the lowest error margin with a final MAPE of 6.45%. This superior performance underscores the robustness of fuzzy logic in effectively modeling non-linear fluctuations and linguistic uncertainties inherent in daily network traffic data, making it an exceptional framework for proactive bandwidth capacity management.

However, while the current research provides strong empirical evidence supporting the integration of FTS for network demand forecasting, several avenues remain open for future investigation to enhance prediction limits and adaptability. First, future studies could explore the implementation of hybrid forecasting architectures, such as combining FTS with machine learning techniques like Long Short-Term Memory (LSTM) networks or Support Vector Regression (SVR), to capture both fuzzy linguistic patterns and complex deep-learning temporal dependencies. Second, the model's scalability could be tested by expanding the dataset to incorporate high-frequency data (e.g., hourly utilization) or by adding external exogenous variables such as public holidays, institutional calendar events, or unexpected network anomalies. Lastly, integrating an automated optimization algorithm, such as Particle Swarm Optimization (PSO) or Genetic Algorithms (GA), to dynamically determine the optimal length of intervals in the FTS process could further minimize forecasting errors and streamline infrastructure planning.

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Appendix

Appendix A. The Dataset and the Prediction Results for Data Bandwidth Needs

Appendix A1. The dataset and the prediction results for data bandwidth needs.

Date	Data Actual	Fuzzified	Forecasted	MAPE
February 1, 2019	28091	U_6	-	-
February 4, 2019	27890	U_5	27900	0.03
February 5, 2019	26754	U_5	25905	3.17
February 6, 2019	25434	U_4	25905	1.85

Date	Data Actual	Fuzzified	Forecasted	MAPE
February 7, 2019	29308	U_6	27460	6.30
February 8, 2019	27338	U_5	27900	2.05
February 11, 2019	29558	U_6	25905	12.35
February 12, 2019	28784	U_6	27900	3.07
February 13, 2019	29096	U_6	27900	4.11
February 14, 2019	27145	U_5	27900	2.77
February 15, 2019	28909	U_6	25905	10.38
February 18, 2019	28573	U_6	27900	2.35
February 19, 2019	28335	U_6	27900	1.53
February 20, 2019	27246	U_5	27900	2.39
February 21, 2019	26368	U_5	25905	1.75
February 22, 2019	24514	U_3	25905	5.68
February 25, 2019	22705	U_2	25438	12.04
February 26, 2019	27016	U_5	27199	0.675
February 27, 2019	29915	U_7	25905	13.40
February 28, 2019	26393	U_5	26612	0.83
March 1, 2019	27928	U_5	25905	7.24
March 4, 2019	28955	U_6	25905	10.53
March 5, 2019	28353	U_6	27900	1.59
March 6, 2019	27451	U_5	27900	1.63
March 7, 2019	29892	U_7	25905	13.33
March 8, 2019	23177	U_3	26612	14.81
March 11, 2019	27398	U_5	25438	7.15
March 12, 2019	25029	U_4	25905	3.50
March 13, 2019	30166	U_7	27460	8.97
March 14, 2019	29802	U_6	26612	10.70
March 15, 2019	29919	U_7	27900	6.74
March 18, 2019	28652	U_6	26612	7.12
March 19, 2019	28248	U_6	27900	1.23
March 20, 2019	25270	U_4	27900	10.40
March 21, 2019	26450	U_5	27460	3.81
April 1, 2019	28142	U_6	25905	7.94
April 2, 2019	29040	U_6	27900	3.92
April 3, 2019	26515	U_5	27900	5.22
April 4, 2019	23732	U_3	25905	9.15
April 5, 2019	28490	U_6	25438	10.71
April 8, 2019	26961	U_5	27900	3.48
April 9, 2019	27391	U_5	25905	5.42
April 10, 2019	29224	U_6	25905	11.35
April 11, 2019	25059	U_4	27900	11.33
April 12, 2019	28994	U_6	27460	5.29
April 15, 2019	25583	U_4	27900	9.05
April 16, 2019	27156	U_5	27460	1.11
April 17, 2019	26775	U_5	25905	3.24
April 18, 2019	19276	U_1	25905	34.39
April 19, 2019	25438	U_4	25438	0
April 22, 2019	24179	U_3	27460	13.56
April 23, 2019	25292	U_4	25438	0.57
April 24, 2019	29080	U_6	27460	5.57
April 25, 2019	24797	U_4	27900	12.51
April 26, 2019	24137	U_3	27460	13.76
April 29, 2019	23498	U_3	25438	8.25
April 30, 2019	-	-	25438	-