An Empirical Study on Internet Traffic Prediction Using Statistical Rolling Model

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Abstract—Real-world IP network traffic is susceptible to external and internal factors such as new Internet service integration, traffic migration, internet application, etc. Due to these factors, the actual Internet traffic is non-linear and challenging to analyze using a statistical model for future prediction. In this paper, we investigated and evaluated the performance of different statistical prediction models for real IP network traffic; and showed a significant improvement in prediction using the rolling prediction technique. Initially, a set of best hyper-parameters for the corresponding prediction model is identified by analyzing the traffic characteristics and implementing a grid search algorithm based on the minimum Akaike Information Criterion (AIC). Then, we performed a comparative performance analysis among AutoRegressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), SARIMA with eXogenous factors (SARIMAX), and Holt-Winter for single-step prediction. The seasonality of our traffic has been explicitly modeled using SARIMA, which reduces the rolling prediction Mean Average Percentage Error (MAPE) by more than 4% compared to ARIMA ( incapable of handling the seasonality). We further improved traffic prediction using SARIMAX to learn different exogenous factors extracted from the original traffic, which yielded the best rolling prediction results with a MAPE of 6.83%. Finally, we applied the exponential smoothing technique to handle the variability in traffic following the Holt-Winter model, which exhibited a better prediction than ARIMA (around 1.5% less MAPE). The rolling prediction technique reduced prediction error using real Internet Service Provider (ISP) traffic data by more than 50% compared to the standard prediction method.

Index Terms—IP traffic prediction, ISP, internet traffic, rolling prediction, statistical model

I. INTRODUCTION

Internet traffic engineering deals with the technology, principle, technique, and tool that assist network administrators in evaluating and optimizing the operational IP network performance. Also the traffic prediction and forecasting are some of the most crucial parts affecting network performance [1]. It helps enhance the network Quality of Service (QoS) and Quality of Experience (QoE). Also, traffic forecasting assists ISP providers in their business decisions such as new product development and service decommissions, advertising, pricing, traffic migration, etc., based on traffic forecasting results. In addition, accurate forecasting helps service providers in capacity planning and investment optimization. Therefore, selecting an appropriate methodology for network traffic prediction is critical for ISP business.

Currently, ISP providers highly depend on experienced network administrators, and they follow an instinctive approach to forecast future traffic using the market analysis data such as a possible number of customers and their usage behavior [2]. The factors they considered for their prediction can be divided into two main categories: internal and external factors. Internal factors are related to ISP companies, such as introducing new services, traffic migration, speed up-gradation, etc. In contrast, external factors come from outside, such as new internet applications, regional economic factors, seasonal effects, etc. Therefore, the intuitive method can only predict a rough estimation of future traffic, which is inadequate to make business decisions.

On the other hand, Operational Research, Statistics, and Computer Science contributions led to reliable prediction methods that replaced intuition-based ones. In particular, Time Series Forecasting (TSF), also termed as univariate forecasting, discusses scientific ways to predict chronologically ordered data, called time-series data [3]. The ultimate objective of TSF is to model a complex forecasting system, predicting future behavior based on the historical observation. The TSF models can be categorized into three main categories based on their learning techniques: statistical model, machine learning, and deep learning model. The prediction model from these categories requires historical data to learn the general trend in time series and make inferences about the future. The learning models also demand different settings of hyper-parameters based on the dataset size and complexity. The prediction model’s learning capability and accuracy directly rely on these parameter configurations.

Traditional statistical forecasting models such as Auto-Regressive (AR), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), AutoRegressive Integrated Moving Average (ARIMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors (SARIMAX), Holt-Winter, etc., were studied extensively at different time-series domains. These classical models have been used in traffic load forecasting [4], cloud traffic prediction [5], electricity load forecasting [6], and so on. However, the statistical models are best at capturing the Linear and Short Range Dependencies (SRD) in time-series data but exhibit the least performance in handling...
Long Range Dependencies (LRD), which results in poor time-series prediction and forecasting [7]. In addition, they are also incapable of learning the non-linear attribute of the time-series data. As a result, many variations of the classical forecasting model such as Fractionally Integrated Autoregressive Moving Average (FARIMA) [8], or hybrid models such as ARIMA-GARCH [9] have been proposed to improve the statistical forecasting model’s performance. This research explored several state-of-the-art statistical prediction methods such as ARIMA, SARIMA, SARIMAX, and Holt-Winter to predict internet traffic volume. Also, we implemented a technique called rolling prediction to improve the performance of the standard prediction. In rolling prediction, the model used the validation data of the recent prediction for re-training the corresponding model. The comparative analysis among different prediction models summarizes their overall performance in traffic prediction. This research shows a significant improvement in traffic prediction using the rolling technique for our statistical prediction models. The main contributions of this work are as follows:

- A comparative performance analysis between classical forecasting model in traffic prediction.
- Extracting new features from time series data for better prediction.
- Achieved significant performance improvement for the traditional model by applying the rolling prediction technique.

This paper is organized as follows. Section II describes the literature review of current traffic prediction using statistical models. Section III presents the proposed methodology introducing the rolling prediction model to the traditional model. Section IV presents the performance results of the different prediction methods and draws a comparative picture between standard prediction and rolling prediction. Finally, section V concludes our paper and sheds light on future research directions.

II. LITERATURE REVIEW

Khashi and Bijari [10] proposed an ensemble forecasting model to improve accuracy. Their model is comprised of a statistical model called Auto-Regressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) model. They identified the limitation of the ANN model in handling linear data, which motivated them to apply a hybrid model based on Multi-Layer Perceptron (MLP) to process the non-linear part of the time-series data. ARIMA model handles the linear component in the time series data. A hybrid forecasting model [10] combining the ARIMA and ANN has been developed to improve overall forecasting accuracy. Their model has been tested on three well-known data sets and indicated an improved performance for all of them. The first stage of their methodology was to generate the required data using the ARIMA model, and then this data is fed into the ANN model to predict the future. U. Kumar and V. Jain [11] investigated the performance of the Auto-Regressive Moving Average (ARMA) and ARIMA model to predict the future in advance. They fine-tune the model parameters $p$, $q$, and $d$ by experimenting with different information criteria such as AIC (Akaike Information Criterion), HIC (Hannon–Quinn Information Criterion), BIC (Bayesian Information criterion), and FPE (Final Prediction Error). They also consider AutoCorrelation function (ACF) and Partial AutoCorrelation Function (PACF) plot information to identify the best performing model. Different model performance evaluation metric such as MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error) has been considered in their work. M. Dastorani et al. [12] performed a comparative analysis among different statistical models such AR (Auto-Regressive), MA (Moving Average), ARMA, ARIMA, and SARIMA. They decomposed the original time series to process the random component using AR, MA, and ARMA models. A trial and error approach has been adapted in their research to find out the best-performing model, and they identified the stochastic model most appropriate for their problem. H. Liu et al. [13] compared the performance of two different hybrid models such as ARIMA-ANN and ARIMA-Kalman. These models have been applied to process the non-stationary data, and both showed better performance. The ARIMA part of the hybrid model is used to identify the architecture of the ANN in the case of the ARIMA-ANN model. In contrast, it is used to initialize the Kalman measurement for the ARIMA-Kalman model. Huda M. A. El Hag and Sami M. Sharif [14] identified the weakness of the ARIMA model in long-term prediction and suggested an adjustment in the ARIMA model to solve the problem. Their proposed Adjusted ARIMA (AARIMA) model can handle an extra parameter called self-similarity compared to the traditional ARIMA model. They used four different Hurst estimators to calculate the self-similarity. Their proposed model shows better hourly internet traffic prediction in comparison with the ARIMA model. The modification of conventional statistical models or their combination has been proposed earlier to improve the prediction in internet traffic based on the publicly available dataset. In this research, we focused on improving the performance of internet traffic prediction by adapting a new training strategy instead of modifying or combining the state-of-the-art statistical models. Our experiment results show a substantial performance improvement in traffic prediction after applying the new training strategy.

III. METHODOLOGY

In this section, we first introduce the real IP traffic dataset used in our experiment in subsection III-A. The data requires some preprocessing steps explained in subsection III-B to clean and make it compatible with the prediction model. Then, we describe the feature extraction techniques to extricate the exogenous attributes from our original dataset in subsection III-C. Next, the rolling prediction method that significantly improves our model accuracy is introduced in the subsection III-D. After that, we explain the mathematical background of the prediction model and the performance metric to evaluate them in subsection III-E and III-F respectively. Finally, we
summarize the configuration of our experimental environment in subsection III-G.

A. Dataset

Real internet traffic telemetry on several high speed interface have been used for this experiment. The data are collected every five minutes for a recent thirty-day period. The data contains average generated traffic per five minutes in bit per second (bps). There are 8563 data samples in our dataset consisting of 29 days complete (288 data instances per day) and last day incomplete data (211 data instance for 30th day).

B. Data Preprocessing

The dataset consists of time series data for the entire thirty days collected at every 5 minutes interval. The original dataset was collected in the JSON format, which is incompatible for processing using the prediction model. So, it was converted into CSV format first before starting the model prediction. Only the timestamp (GMT) and traffic data (bps) are taken from the JSON file, and all other information is discarded. The last day data in the dataset is incomplete by the previous eight hours (approximately) data and is removed from the original time series data for the experiment. Ultimately, a total of 29 days of data were considered for developing our prediction model. In addition, there are some missing values in the dataset filled up using the mean value. Finally, the time series value unit has been changed from bps to Gbps (gigabit per second) as the original value is large for feeding into our statistical model.

C. Feature Extraction

Feature engineering is an essential part of any prediction model, whether a statistical or machine learning model. Some features have been derived from the time series data for better prediction. We divided a day into a total seven different portion as mid-night (12 am-3 pm), late-night (3 am-6 am), early morning (6 am - 9 am), morning (9 am - 12 am), afternoon (12 pm -15 pm), late afternoon (15 pm - 18 pm), evening (18 pm - 21 pm), night (21 pm - 24 pm). We introduce another feature based on weekdays and weekends since there is a chance of high traffic on weekdays. These features are particularly provided in the SARIMAX model as it is capable of handling exogenous attributes.

D. Rolling Prediction

Our dataset is divided into train and test sets for training and evaluating the prediction model, respectively. The proposed model used a prediction function, which takes the testing data indices as a parameter for immediate prediction. We looped through our test set entries to make inferences for all test instances. After evaluating each test instance, the model has been re-trained using the true observation from the test set in rolling prediction. In contrast, the standard prediction technique estimates all predictions in the test set after training the model once. This rolling prediction technique exhibits improved performance for all prediction models.

E. Time Series Forecasting Models

1) ARIMA: ARIMA model was proposed by Box and Jenkins and is also known as the Box-Jenkins methodology. This model predicts the future value based on the past values of the time series, that is, its own lagged values and the lagged forecast white noises. The time series need to be stationary before applying the ARIMA model as it performs well when there is no correlation and dependency among the predictors [15]. Total of three parameters, such as order of AR term (p), order of MA term (q), and the number of differencing to make the time series stationary (d) are required to design the ARIMA \((p,q,d)\) model. We can express the ARIMA model mathematically as follow [16]:

\[
\Phi(L)^p \Delta^d y_t = \Phi(L)^q \Delta^d \epsilon_t
\]

\[
\Delta^d y_t = y_t^{d-1} - y_{t-1}^{d-1}
\]

Here, \(y_t\) is the time series.

- \(p, d,\) and \(q\) are referred to as the order of AR, I and MA components of the ARIMA model.
- \(\Delta^d\) is an operator to make the \(y_t\) stationary.
- \(\Phi(L)^p\) id the lag polynomials of order \(p,\) and \(L\) is defined as the lag operator.
- \(\epsilon_t\) is white noise.

2) SARIMA: SARIMA is a generalized version of the ARIMA model which can handle the seasonality in the time series data. The SARIMA model requires additional four parameters such as seasonal autoregressive order \((P)\), seasonal moving average order \((Q)\), the seasonal difference \((D)\), and the length of the seasonality period \((S)\) to process the seasonal component in the series. As a result, six parameters are necessary to define the SARIMA model where \(p, d,\) and \(q\) are the same as the ARIMA model. We can express SARIMA using the following mathematical equation [17].

\[
\Phi(L)^p \Phi(L^S)^P \Delta^d y_t \Delta^D S y_t = \Phi(L)^q \Phi(L^S)^Q \Delta^d \epsilon_t \Delta^D S \epsilon_t
\]

\[
\Delta^d y_t = y_t^{d-1} - y_{t-1}^{d-1}
\]

Here, \(y_t\) is a time series with seasonality \(S\).

- \(P, D,\) and \(Q\) represent the similar meaning of \(p, q,\) and \(d\) in the ARIMA model but rather applicable for seasonal lags.

3) SARIMAX: SARIMAX model capable of processing the exogenous features of the time series. The exogenous attribute calculated at time \(t\) impacts the not auto-regressive time series value at time \(t\). We can change the SARIMA equation [3] above to make it an equivalent SARIMAX equation as follows [18].

\[
\Phi(L)^p \Phi(L^S)^P \Delta^d y_t \Delta^D S y_t = \Phi(L)^q \Phi(L^S)^Q \Delta^d \epsilon_t \Delta^D S \epsilon_t + \sum_{i=1}^{n} \beta_i x_i^t
\]

Here, \(x_i^t\) is the exogenous attribute at time \(t\) and \(n\) is the total number of exogenous features.

- \(\beta_i\) is the coefficient for the variable \(x_i\).
4) Holt-Winter: The Holt-Winters method is also known as Triple Exponential Smoothing, one of the popular algorithms designed for time-series forecasting. The first studies of Exponential Smoothing are back to the Simeon Poisson; after him in 1956, Robert Brown has introduced its forecasting application. This forecasting model is defined in three equations one for level ($l_t$), one for trend ($b_t$), and one for seasonality ($s_t$) and also forecasting equation with smoothing parameters $\alpha$, $\beta$, and $\gamma$, respectively. Holt-Winters method has two variations, additive and multiplicative, that differ like the seasonal data values. We used an additive version of the Holt-Winter model for our experiment, and the equation can be defined as follow [19]:

$$l_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1})$$  (6)

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}$$  (7)

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m}$$  (8)

$$\tilde{y}_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)}$$  (9)

- Here, $m$ represents seasonal period.
- $\beta_i$ is the coefficient for the variable $x_i$
- $h$ is forecast horizon
- $k$ is the integer part of $(h - 1)/m$.

F. Evaluation Metrics

We used Mean Absolute Percentage Error (MAPE), to estimate the performance of our traffic forecasting models. The performance metric identify the deviation of the predicted result from the original data. For example, MAPE error represents the average percentage of fluctuation between the actual value and predicted value. Therefore, we can define our performance metric mathematically as follow:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{p_i - o_i}{o_i} \right| \times 100\%$$  (10)

Here, $p_i$ and $o_i$ are predicted and original value respectively, and $n$ is the total number of test instance

G. Software and Hardware Preliminaries

We have used Python and the statistical model library statsmodels [20] to conduct the experiments. Our computer has the configuration of Intel (R) i3-8130U CPU@2.20GHz, 8GB memory, and a 64-bit Windows operating system.

| SL | (p, d, q) | AIC |
|----|----------|-----|
| 1  | (13, 1, 16) | 3782.588307 |
| 2  | (21, 1, 2) | 3782.751381 |
| 3  | (14, 1, 17) | 3783.706900 |
| 4  | (13, 1, 18) | 3785.061129 |
| 5  | (21, 1, 3) | 3785.332434 |
| 6  | (22, 1, 3) | 3786.325772 |
| 7  | (16, 1, 17) | 3786.547150 |
| 8  | (17, 1, 17) | 3786.761965 |
| 9  | (22, 1, 4) | 3786.964070 |
| 10 | (20, 1, 2) | 3787.326614 |

TABLE II: Performance summary for all model

| Model      | MAPE (Standard Prediction) | MAPE (Rolling Prediction) |
|------------|-----------------------------|---------------------------|
| ARIMA      | 20.09%                      | 7.71%                     |
| SARIMA     | 21.03%                      | 7.34%                     |
| SARIMAX    | 21.58%                      | 6.83%                     |
| Holt-Winter| 18.29%                      | 7.59%                     |
TABLE III: Comparison between actual traffic and predicted traffic

| Prediction Model | Prediction | Rolling Prediction |
|------------------|------------|-------------------|
| ARIMA            | ![Graph](image-url) | ![Graph](image-url) |
| SARIMA           | ![Graph](image-url) | ![Graph](image-url) |
| SARIMAX          | ![Graph](image-url) | ![Graph](image-url) |
| Holt-Winter      | ![Graph](image-url) | ![Graph](image-url) |

After that, we plotted the ACF and PACF in Fig. 2 to figure out the hyper-parameters $p$ and $q$ for the ARIMA model. It is difficult to define AR($p$) and MA($q$) order from these plots as there is a sinusoidal pattern and no clear indication of the lag, which is significant for our time series data. That is why a grid search technique has been applied to identify the best hyper-parameter combination of $p$, $q$, and $d$ based on the minimum Akaike Information Criterion (AIC) value. We tested different $p$ and $q$ combinations from 0 to 24 with difference order 1 to find the best parameter set for our ARIMA model. The top ten combinations based on minimum AIC value are shown in Table II. Our grid search result indicates the order (13, 1, 16) is the best combination with minimum AIC of 3782.588307 for the ARIMA model. Similarly, the best model parameter we identified for SARIMA model is $(p, d, q) = (13, 1, 16)$ and $(P, D, Q, S) = (1, 0, 1, 24)$. The best performing parameter for SARIMAX model is $(p, d, q) = (13, 1, 16)$ and $(P, D, Q, S) = (1, 0, 1, 24)$. We also provided the exogenous features extracted from our original traffic data according to the feature extraction process discussed in subsection III-C into the SARIMAX model. Finally, we fine-tuned three hyper-parameters parameters for the Holt-Winter model: trend type, seasonality type, and seasonality period. The additive version of the Holt-Winter model is used in our experiment since the seasonal variation is relatively constant over time.

We experimented with two different types of prediction
methodology. The standard prediction method is mainly divided into two stages: train and test. But rolling prediction model used the validation data of the latest prediction to retrain the model after each inference. The result presented in Table III shows improved performance for all models in rolling prediction if we compare it with standard prediction. The model performance evaluation metrics MAPE in standard prediction decreased to more than 50% in rolling prediction for every model. Firstly, we applied ARIMA model with the best parameter combination \( (p = 13, d = 1, q = 16) \), and it resulted in average percentage prediction error of 7.71 Gbps. Since ARIMA cannot handle the seasonality in the time-series data, we implemented another model, SARIMA, accepting seasonality information as a hyper-parameter. SARIMA provides better results with a 7.34% average deviation from the original traffic in the rolling prediction, reducing the prediction error by more than 4% compared to ARIMA. Next, we extracted some features from our original dataset according to the feature extraction process described in section III-C. The original traffic and their exogenous attributes are then trained using SARIMAX, which can handle extra features along with traffic seasonality. The SARIMAX yields the best prediction result in our experiment with the lowest MAPE of 6.83%, decreasing the error by more than 11% and 6% compared to ARIMA and SARIMA, respectively. Finally, we implement Holt-Winter prediction model to handle the variability in our traffic data by using the exponential smoothing technique. The Holt-Winter shows 7.59% average fluctuation between predicted and actual traffic using rolling prediction, and it is 1.5% less error than ARIMA. Our best-performing model SARIMAX reduces the prediction error by more than 10% in comparison to the Holt-winter. In Table III we depicted the actual and expected traffic for the last eight days using both standard prediction and rolling prediction. The comparison between actual and predicted traffic shows a significantly better fitting using the rolling prediction technique.

V. Conclusion

In this research, we experimented with several internet traffic prediction models. We tried to improve the performance of state-of-the-art prediction models to learn the general trend in real IP traffic. Also, a comparative performance analysis among several conventional statistical models has been conducted in traffic prediction. Our experimental results show a significant improvement in traffic prediction when we feed our model with the validation data after each prediction. We considered four different prediction models, e.g., ARIMA, SARIMA, SARIMAX, and Holt-Winter, showing a better accuracy using the rolling prediction technique than the standard prediction. As part of our future work, we would like to model the residual variation using Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH). Also, we plan to extend our work from single-step traffic prediction to multi-step prediction.

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