Estimating and Forecasting Network Traffic Performance based on Statistical Patterns Observed in SNMP data.

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Abstract. With scientific data growing to unprecedented volumes and the needs to share such massive amounts of data by increasing numbers of geographically distributed collaborators, the best possible network performance is required for efficient data access. Estimating the network traffic performance for a given time window with a probabilistic tolerance enables better data routing and transfers that is particularly important for large scientific data movements, which can be found in almost every scientific domain. In this paper, we develop a network performance estimation model based on statistical time series approach, to improve the efficiency of network resource utilization and data transfer scheduling and management over networks. Seasonal adjustment procedures are developed for identification of the cycling period and patterns, seasonal adjustment and diagnostics. Compared to the traditional time series models, we show a better forecast performance in our seasonal adjustment model with narrow confidence intervals.

Keywords: Time series, Seasonal Adjustment, Network Traffic Forecast, STL, X12-ARIMA

1 INTRODUCTION

The analysis of network traffic is getting more and more important today to efficiently utilize the limited resources offered by network infrastructure and wisely plan the large data transfers. Estimating the network traffic for a given time window with a given probabilistic tolerance error enables better data routing and transfers, which is particularly important for large scientific data movements. Short-term prediction of network traffic guides the several immediate scientific data placement. Long-term forecast of network traffic evaluates the performance of network and enables the capacity planning of the network infrastructure up to the future needs.

The problem of analysis of network traffic has received attention over the years. Previous researches about network traffic can be distinguished in two categories: frequency-domain methods including spectral analysis and wavelet analysis [23] and time-domain methods including auto-correlation and cross-correlation analysis [5]. Besides the main stream models such as time-domain models ARIMA, FARIMA or frequency-domain methods wavelet analysis, there are also learning approach methods [1,18].

However, one very important feature in the time series is the periodicity or seasonality [10]. The seasonal variation is a component of a time series and occurs as a repetitive and predictable movement around the trend line in one time cycle. Organizations such as manufacturing industry with quarterly assignment adjust their performance relative to normal seasonal variation. In the census data released by U.S. Census Bureau, many indexes are seasonally adjusted to monitor the general trend without the influence of periodical changes. For example, the unemployment rate is expected to increase in every June because of the recent graduates entering the job market. However, the overall unemployment rate should be evaluated after removing the expected seasonality for this June effect. Seasonal movements are often large enough to mask other characteristics of the data such as current trends. For example, if each month has a different seasonal tendency toward high or low values, it could be difficult to detect the general direction of a recent monthly movement in the time series (increase, decrease, turning point, no change, consistency with another economic indicator, etc.). With seasonal adjustment removing seasonal component from the original series, seasonally adjusted series would reveal the recent trend without obscuration from the seasonality, and its relationship with other different series can be easily measured. However, the periodicity in the network traffic has never been explored in our knowledge, and the modeling based on periodicity has never been applied to the analysis and forecast of network traffic. From our analysis, the network traffic measurement data, SNMP shows significant periodical behavior. In Figure 1, the periodicity of network traffic within a day is shown, based on the seasonality of the 1-year SNMP data, and the trend component shows the general change in the original series while the irregular component shows the collection of the random behavior in network usage.

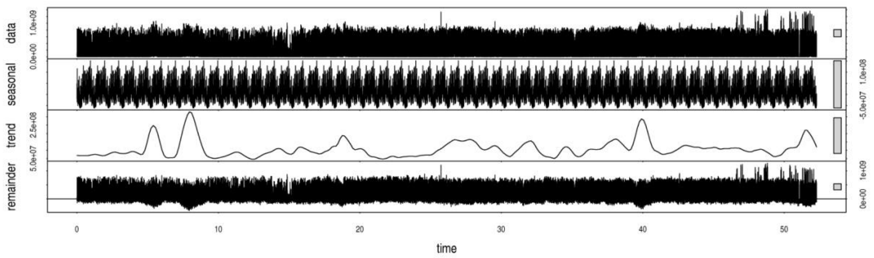


Fig. 1. Periodicity in network traffic data. Original series, seasonal component, trend component and irregular/remainder component from the top to the bottom.

Figure 1 is the result of seasonal adjustment, which decomposes the original series into three components: S (Seasonal Component), I (Irregular Component), and T (Trend Component). The seasonal component is the second plot in Figure 1 which models the undergoing specific variations at certain moments during one cycling period. It usually combines features of regular behavior of network usage and routine data transfer. The third plot is trend component which shows the long-term change from general phenomena, and it fits our interest in estimating the current situation and predicting future condition. We could find the illustrated series has a general trend that involves high volume network traffic at the beginning and the end of the observation range. The last plot is irregular component which models the unexpected behavior from the statistical errors or from the nonrecurring accidental or fortuitous events. It is usually assumed to follow a normal distribution and outliers can be detected by p-values.

In this paper, we will address two challenges in the network performance modeling with STL and seasonal adjustment: 1. Seasonality in the network measurement data has not been addressed before in our knowledge, and we will show our findings from the evaluation results from three criterion indexes and diagnostic results supporting the existence of seasonality in the network measurement data. 2. The periodicity in the network measurement data is unknown. STL and seasonal adjustment methods cannot be used without the periodicity of the time series. We studied three criterions to select the best periodicity to generate the prediction with the least forecast error and the full extraction of the seasonal/periodical pattern in the measurement data.

In this paper, we focus on finding and modeling the periodical patterns in the network traffic, and discuss the procedure of seasonal adjustment methods on network traffic measurement data. Unlike general social data, the cycling period is unknown in the network traffic data. In section 2, we discuss the identification of the significant cycling period of the network traffic measurement data, two seasonal adjustment methods, X12-ARIMA and STL, and the validation methods with seasonal adjustment. In section 3, we discuss the results of analysis, and evaluate the performance of the prediction model. In section 4, we conclude our results with comparison of our models to the results from two methods, ARIMA and wavelet-based methods.

2 PERIODICITY AND SEASONAL ADJUSTMENT

2.1 Criterion to Identify Periodicity

Most social data shows seasonal periodical patterns. In agricultural industry, we can find a seasonality of sowing and harvesting in a yearly cycle. In banking industry, we can find a seasonality of savings amount increasing at the beginning and decreasing at the end in a monthly cycle. In highway transportation traffic, you can find a seasonality of rush hours in a daily period. However, periodicity of network traffic is unknown, and network measurement data is collected more frequently, compared to other social data, in about every 30 seconds for SNMP measurements. In order to apply seasonal adjustment, the cycling period needs to be determined.

We evaluate the data based on different cycling period according to three criterions:

1. Identified seasonality: A cycling period is determined within the period that can be identified with significant seasonality. This feature in our model is used to provide better prediction.
2. Residual seasonality: The seasonally adjusted data series is the residual data that seasonal components are subtracted from the original data series. Residual seasonality is not expected in the seasonally adjusted data series.
3. Log transformation: Log transformation was applied to provide stationary data over time, for old data, recent historical data as well as newly acquired data.

Seasonality detection methods were used for the first two criterions. Log transformation was determined by how the data is stationary.

Seasonality Detection

The seasonality detection methods are divided into two groups: graphical techniques and statistics based on Seasonal Index measures. The graphical techniques include run sequence plot, seasonal subseries plot, multiple box plots and autocorrelation plot. The significance of seasonality is determined based on the plot by the human eyes, and it is often subjective. For an automated procedure of the seasonal adjustment, the statistical method based on seasonal index measures is selected in our model. Our analysis used two diagnostic methods, the F-test for the presence of seasonality [12] and M7 for X11-ARIMA [17].

Log-Transformation

The log transformation based on the log-likelihood test is to stabilize the variance, so that the data can be modeled with the Box-Jenkins methodology [2]. The model is derived with the log-transformed data and the original data to obtain the maximum likelihood. Log transformation is applied when the model has larger likelihood based on the transformed data.

After evaluating periodicity for the network traffic measurement data, the network traffic data is organized into a time frame with the determined cycle.

2.2 Seasonal Adjustment

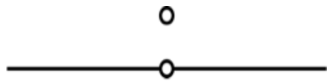
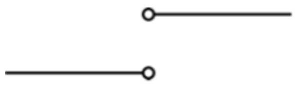
Missing Value Treatment

Before the seasonal adjustment methods are applied, any missing values and identifying outliers in network traffic measurement data are treated. Some of the network traffic data are lost due to failures on the collection device. The rate of the missing values in our data is around 0.7%, but missing values may cause an increase in the forecast error, especially when recent records are missing. The recent activities of nearby data points and the feature of its cycling period are considered for the replacement methods for missing values, and they are estimated by a weighted average of the recent data points and the points falling into the same cyclic spots within every period.

$$\widehat{x_{tk+p}} = \sum_{i=tk}^{tk+2p} \alpha_i x_i + \sum_{j=1}^{C} \beta_j x_{tj+p}$$

where $\sum_{i=tk}^{tk+2p} \alpha_i + \sum_{j=1}^{C} \beta_j = 1$, t is the length of every cycling period, k represents the kth cycle where the missing value is found, p represents the pth spot where the missing value is found, and C is the total number of cycles in the period. $\sum_{i=tk}^{tk+2p} \alpha_i x_i$ represents the influence of the recent activity to the missing point, and $\sum_{j=1}^{C} \beta_j x_{tj+p}$ represents the periodicity occurred in the data series. The weighted average coefficients α_i and β_j would be selected as the closer activities are more related to the missing point. The missing value x_{tk+p} occurred in *p*th spot in kth cycle would be replaced by its estimated weighted average $\widehat{x_{tk+p}}$.

Table 1. Illustration of Four Types of Regressors

AO	LS
	
TC	RP
	

Outlier Detection

The outliers are recorded, rather than being replaced, by its value, time and type. The four types of records are AO (Additive outliers), LS (Level Shift), TC (Temporary Change) and RP (Ramps) as shown in Table 1. The outlier data series is used in the RegARIMA for X12-ARIMA method.

$$\log(Y_t) = \beta' X_t + Z_t$$

where the log transformation is based on the stable variation, Z_t is the ARIMA process, Y_t is the original series, and X_t is the regressor of outlier data series.

AO: if t_0 is an addtive outlier, then $X_{AO_t} = \begin{cases} 1 & t = t_0 \\ 0 & t \neq t_0 \end{cases}$

LS: if series shift suddenly at t_0 and continues on new level, $X_{LS_t} = \begin{cases} -1 & t < t_0 \\ 0 & t \geq t_0 \end{cases}$

TC: if series shift suddenly at t_0, then slowly declines to original level.

$X_{TC_t} = \begin{cases} 0 & t < t_0 \\ \alpha^{t-t_0} & t \geq t_0 \end{cases}$ where α is a decreasing rate estimated from data

RP: if series slowly change to a new level start from t_0 and end by t_1,

$$X_{RP_t} = \begin{cases} -1 & t < t_0 \\ \dfrac{t - t_0}{t_1 - t_0} - 1 & t_0 \leq t < t_1 \\ 0 & t \geq t_1 \end{cases}$$

For a seasonal-trend decomposition procedure based on Loess (STL) [3], the extreme values are modified to be robust in the iteration of STL algorithm. The distortion of extreme values would be limited in the modeling and forecasting, but its influence would remain in the data series for hidden information.

Seasonal Adjustment Methods

Two seasonal adjustment methods are applied to the network traffic measurement data, a seasonal-trend decomposition procedure based on Loess (STL) and the X12-ARIMA [21,22].

X12-ARIMA includes a group of calendar effects that the network traffic measurement data does not show, and the regressors that only fit the characteristics of network traffic must be selected. The network traffic measurement data fluctuates frequently, compared to the social data, due to the dynamic network data transfer features, and the outliers that are represented by large data transfers are likely to occur in random. The special characteristics of network traffic should be considered in the X12-ARIMA regression model for the frequent changing patterns and more aberrant events.

After the seasonal adjustment on the network traffic measurement data, the data will be decomposed into three components: trend, seasonal and irregular components. The performance of the seasonal adjustment model will be evaluated, and assessed with two diagnostic methods.

2.3 Seasonal Adjustment Diagnostics

The diagnostics of seasonal adjustment examine the stability of adjusted data series with a persistent model for new data feeds, which enables better prediction of network traffic performance. New measurement is collected for the network traffic data, and the model must not be changed frequently causing the computational costs and time. To assess the stability, two diagnostics results are considered from the revisions history diagnostics and the sliding spans diagnostics.

Revision History Diagnostics

The revision history diagnostics [19] create many seasonal adjustments on a sequence of increasing data spans, at a new time point each time. The assessment of stability is based on the evaluation of the magnitude of revisions over time, which parameterizes the model characteristics such as transformation type, performance parameters such as forecast errors, and model evaluation values such as AIC and log-likelihood. Take the adjusted series $\mathrm{A_t}$ as an example, we illustrate how we measure the revision over a period lag.

For a given series $\mathrm{y_t}$ where *t=1,...,T*, we define $\mathrm{A_{t|n}}$ to be the seasonal adjustment of $\mathrm{y_t}$ calculated from the series $\mathrm{y_1, y_2, \ldots, y_n}$, where $\mathrm{t \le n \le T}$. The concurrent seasonal adjustment of observation t is $\mathrm{A_{t|t}}$ and final adjustment is $\mathrm{A_{t|T}}$. The concurrent target captures the lagged revision history where the target is assumed to be the concurrent estimate. Concurrent target $= \frac{A_{t|t+lag} - A_{t|t}}{A_{t|t}}$. If the revision (absolute value of concurrent target) is very large, we consider the model is unstable when we add more data. The final target concurrent gives the lagged revision history where the target is assumed to be the final estimate. Final target $= \frac{A_{t|T} - A_{t|t+lag}}{A_{t|t+lag}}$. If the revision (the absolute value of final target) is too large, we consider the model is unstable when we go back into different time points in history.

Sliding spans diagnostics

The sliding spans diagnostics [9] compare the adjusted results to the overlapping sub spans of the time series, for the stability of the seasonal adjustment. Each span with a length H starts one cycling period after the previous span, where H depends on the choice of seasonal adjustment filters. Seasonal adjustment is applied on each span, and their adjusted results are compared. When the adjusted results would be changed too much across spans, the seasonal adjustment must not have a stable model.

Let A_t denote its seasonally adjusted value obtained from the complete series, and let A_t^j denote the adjusted value obtained from the *j*-th span. Then, the seasonal adjustment A_t is called unacceptably unstable, if

$$\frac{\max_j A_t^j - \min_j A_t^j}{\min_j A_t^j} > 0.03$$

3 Seasonal Adjustment on SNMP data

The SNMP data provides aggregated link usage data, collected every 30 seconds, on the network connections. We have access to publicly available ESnet SNMP data [15], and the time span of these SNMP data is from May 6 18:49:00 PDT 2011 to the present time. In our current studies, we retrieved data up to Jul 25 15:56:30 PDT 2012.

3.1 Periodicity of SNMP data

The potential periodicity for SNMP data can be from as small as one minute to a few months. Figure 2 shows the decomposed series based on periodicity of a week, a day, an hour and a minute. In each plot, four subplots show, in order, original series, seasonal component, trend component and irregular component from the top to the bottom. With a longer periodicity, clearer pattern of seasonality is observed, and the trend component shows smooth curves. The irregular component shows very large variations, and we suspect that many routine events cannot be counted as seasonal component with the large rough cycling period. With a shorter periodicity, the seasonal pattern is not clear, and the trend component changes frequently. However, the irregular component shows a small portion. Seasonal adjustment with a longer periodicity such as a week does not identify a clear seasonality, and a shorter periodicity such as a minute causes the seasonality distorted easily by random events. Table 2 shows the portion of seasonally adjusted components, compared to the original data series.

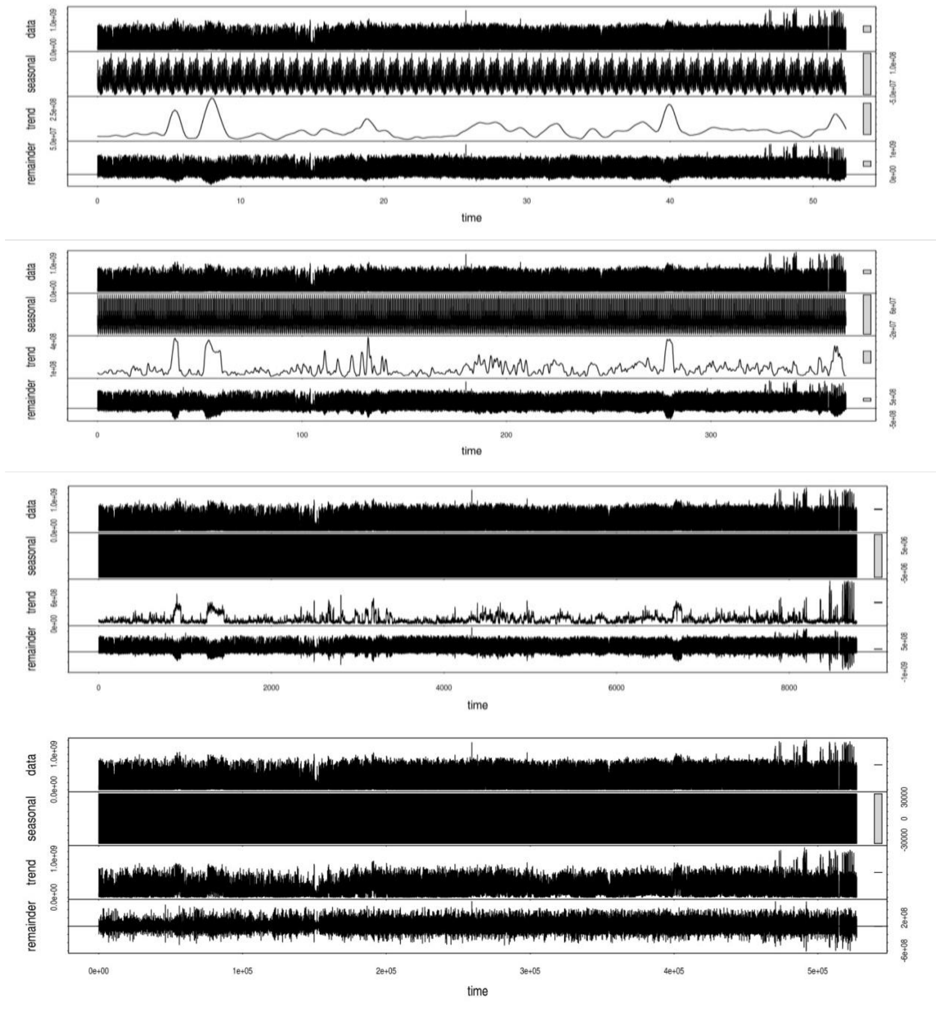


Fig. 2. Seasonal adjustment based on the periodicity of a week, a day, an hour and a minute, from the top to the bottom. Each plot shows four subplots of original series, seasonal component, trend component and irregular component.

Table 2 show that the seasonal and irregular components decrease with a shorter periodicity, and the trend component increases with a shorter periodicity. The seasonal and trend components have the deterministic model for forecasting, and the irregular component has the distribution information on the forecast with a certain level of error, which can be modeled as a normal distribution with a zero mean and a variance. The non-deterministic behavior of irregular component causes the uncertainty in the forecast. For more deterministic information and less randomness, portions of seasonal and trend components should be higher, and the portion of irregular component should be lower. As a trade-off during the periodicity selection, a significant seasonality should be identified while controlling the irregular portion in the model. From Table 2, the best periodicity would be observed between a day and an hour.

Table 2. Portion of seasonally adjusted components

Periodicity	Seasonal	Trend	Irregular
Week	43.2%	44.6%	78.3%
Day	28.1%	69.1%	53.0%
Hour	5.7%	88.5%	29.8%
Minute	0.1%	98.5%	6.8%

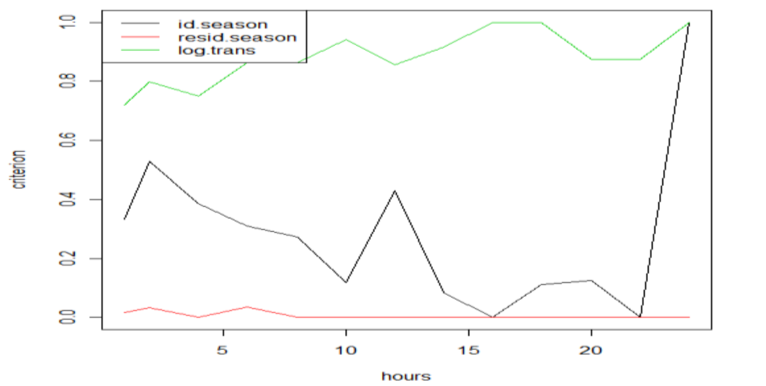


Fig. 3. Seasonal adjustment criterions for different periodicity

Figure 3 shows the seasonal adjustment criterion defined in section 2.1 to evaluate the performance of model with different periodicity. The significant seasonality is observed when the index of the identified seasonality is close to 1. The residual seasonality is close to 0 when the seasonality is fully extracted from the original series and modeled. The log transformation shows stability when the value is close to either 0 or 1. From Figure 3, the optimal period would be based on a day, since the identified seasonality is exactly equal to 1 and the residual seasonality is equal to 0. The model identifies and extracts a significant seasonality effectively. The stability of the seasonal adjustment based on the daily period is strong with the index of “log transformation” as 1. Figure 3 also shows that 12 hours of periodicity indicates low residual seasonality with the relatively higher identified seasonality at 0.4. The log transformation does not indicate the stability as high as the daily periodicity, but the residual seasonality is 0 indicating the model can fully extract the seasonality. This may corresponds to the network activity based on the daily working schedule.

Another significant seasonality is shown in Figure 3 at 2 hours of the periodicity with the identified value at 0.5 and the remaining seasonality close to 0, although the log transformation is valued at 0.8 indicating the model is not stable. From these observations, the optimal cycling period would be determined as a day with significant identified seasonality, zero remaining seasonality in the residuals and stable transformation all the time. When we test the cycling period for different series, the daily period holds best cycling period for 90% series.

3.2 Seasonal adjustment

Based on the periodicity of a day, the seasonal adjustment is applied on the organized time frame of SNMP data.

Figure 4 shows the results from seasonal adjustment based on STL and X12-ARIMA respectively with plots of original series, seasonal, trend and irregular components from the top to the bottom.

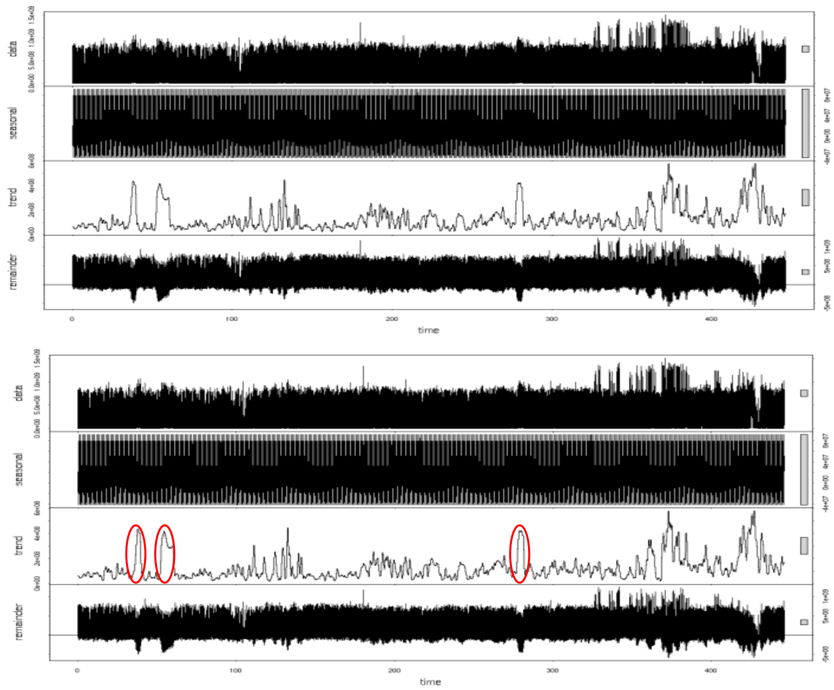


Fig. 4. Seasonally adjusted series based on STL and X12-ARIMA

The STL model derived with 15 outer loops. The span used for “s” (seasonal), “t” (trend) and “l” (loess) is respectively 12841361,4321 and 2881. The weights for observation fall into 1st quantile at 0.7703182 and 3rd quantile at 0.9887374 with median to be 0.9452160. Extreme value in the original series is detected with weight equal to 0. In the final decomposition, the IQR (interquartile range) of seasonal component accounts for 40.5% of the IQR of original series and IQR of trend component is 75.9% of the IQR of original series.

The X12-ARIMA model choice is ARIMA (3 0 0)(0 1 1) with log transformation with regression on identified outliers and an intercept as 0.02. F-test for seasonality has significant F-value 30.383 and suggests seasonality present at 0.1 percent level. The residual seasonality is tested to be no presence at the 1 percent level. The IQR of seasonal component decomposed in X12-ARIMA is 42.5% of the IQR of original series and IQR of trend component is 73.2% of the IQR of original series.

The results obtained from X12-ARIMA and STL show similar decomposed components. The trend component indicates that there are more level shifting occurred at the end of the time series. At the end of time series, more additive outliers are identified. A few temporary changes are observed in the series, and 3 significant ones are identified which is circled red in Figure 4 with a sudden large jump as steep cliff and a single peak last for a while and then a sudden drop back to normal level.

3.3 Diagnostics

The diagnostic tests would validate and examine stability of the model based on the seasonal adjustment. The revision histories diagnostics test the model performance parameters for different time spans, as shown in Figure 5. Plots are shown from Q statistics q/q2, M statistics, log-likelihood and AIC. The dashed lines in each plot indicate the boundary of 20% threshold, as the changes of either performance parameters or forecast error would be limited within 20% of changing interval. Almost all values across time spans stay within the boundary, indicating the stability of the model. Only 1 out of 20 time spans has a value of log-likelihood out of the boundary, and 2 out of 20 time spans have a value of m statistics touching the limit. The diagnostics tests show the stable seasonal adjustment in the model performance evaluation parameters.

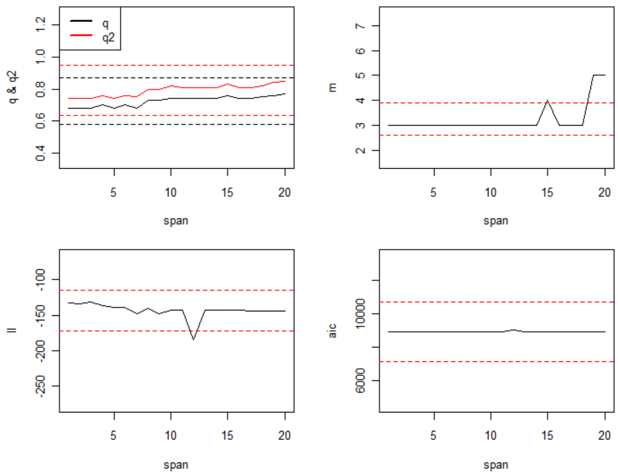


Fig. 5. Diagnostics: model performance

4 Forecast errors

The forecast error can be explored in the model based on X12-ARIMA by estimating the last data cycle from the model based on the data without the last cycle. Similarly, the last two cycles can be estimated by the model based on the data without the last two cycles.

$$\text{Forecast Error} = \frac{\text{Forecast} - \text{True Traffic}}{\text{True Traffic}} * 100\%$$

Figure 6 shows that the forecast errors are less than 20% in most cases, and around 10% in some cases. The forecast error is smaller in the next day prediction, and increases over time because of the uncertainty into the future with less information. The extreme events may cause a spike in the forecast errors, but the forecast errors are still within a good acceptance range.

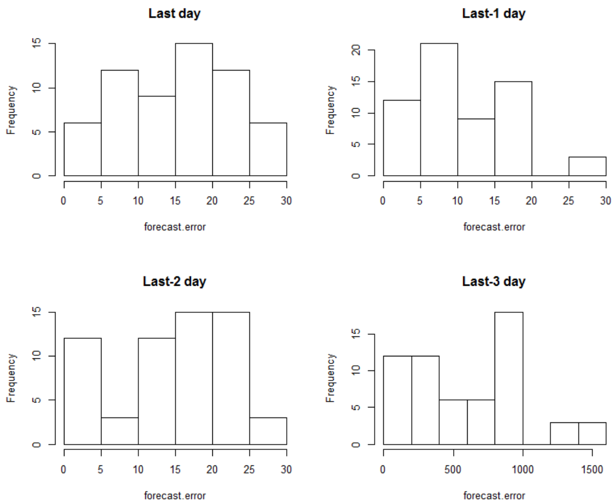


Fig. 6. Forecast error based on X12-ARIMA (%)

In comparison of the forecast performance among 6 different methods: ARIMA model, ETS model, Holt-Winters method, STL model, linear regression model and local level structural model, time series fluctuation is considered in three methods; Holtwinters by minimizing the squared prediction error using Holt-Winters Filtering [13,20], STL and linear regression fit model with explanatory variables as trend and seasonality components. Other methods include ARIMA based on the AIC (Akaike information criterion), Exponential smoothing state space model (ETS) [4,16] based on AIC determine its triplet (E,T,S) which denote additive or multiplicative model for error and trend and the presence of seasonality, and local level structural methods with state-space models [11] fitted by maximum likelihood.

Figure 7 shows the prediction with point estimator and two confidence interval forecasts. The orange shades indicate the 90% confidence interval, and the yellow shared represents the 95% of confidence interval. The forecast by the seasonal adjustment method based on STL offers predictions for seasonal variation, while the traditional ARIMA, ETS and local structure models only give estimators being same all the time without considering fluctuation. The ARIMA, ETS and local structure models do not provide forecasts without using full periodic information in the original data series, when the data show a periodicity. The method based on STL provides the smallest confidence interval among the 6 methods, and the accuracy of the prediction with the seasonal adjustment is better than the rest of the traditional methods. The improvement in the forecast error is mainly because of the new variables in the time series model to explain the original series. The newly added variables include three seasonal components, seasonality, trend and residual, as well as variables of outliers and missing values. These new additions capture more features of the data and generate better prediction for the time series.

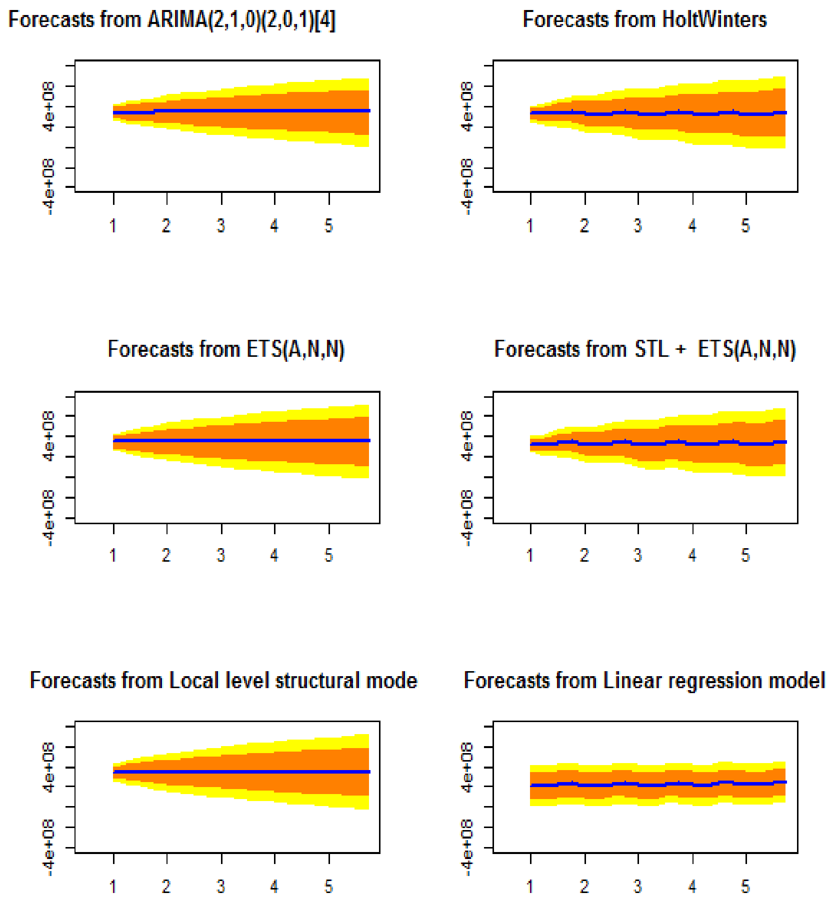


Fig. 7. Compare with other models

5 CONCLUSION AND FUTURE WORK

In this paper, we presented statistical models for estimating and forecasting network traffic based on the statistical patterns found in the network measurement SNMP data. The three steps Seasonal Adjustment procedure will enable us to analyze the seasonality existed in scientific data such as network traffic. We first determine the cycling period with significant seasonality is daily and with application X12-ARIMA and STL we decompose the original series into three components: seasonal component, trend component and irregular component. The diagnostics test is adopted to assess the credibility of our model. The prediction error derived from our model is on average within 20% and it shows superior results in terms of narrower confidence interval with less prediction interval when compared with 6 traditional time series models on network traffic. Our ongoing work includes further explored the usage of the three components resulted from Seasonal Adjustment procedure. To list a few, we will use trend component to trace the data flow over the whole network map and use seasonal component to plan routine data transfer. With combination of all three components, we can plan the future data transfer based on the prediction of network traffic condition. Long-term prediction of future network traffic development could also enable us to wisely allocate the infrastructure and links within the network.

6 ACKNOWLEDGMENTS

This work was supported by the Office of Advanced Scientific Computing Research, Office of Science, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

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