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Time-Series Short-Term Forecast of Internet Traffic

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Abstract. Internet service providers are expected to continuously provide services without interruptions. However, planning for this activity requires several tasks (such as forecasting clients' demand) that need to be considered in fulfilling their objectives particularly in face of calamity. This paper presents the results of using four methods for forecasting the demand of a single client of Internet Service Provider. A total of 1440 points of inbound and outbound traffic bandwidth usage, taken at 30 minute time intervals for two weeks, were used. By visually clustering the traffic and by using different parameters of those forecasting methods, a total of 40 time series combinations were studied. The results of the study indicate that the best short-term forecasting method was the exponential smoothing method with a smoothing parameter α of 0.3. The findings of this study should be of great help to the Internet Service Provider to better plan for load distribution between international links and help in approving down times and maintenance windows requested by cable providers. This should also help in detecting cyber security attacks or spam and reduce clients' complaints, thus improving their quality of service. For future work, we recommend to use close parameter values to possibly improve the forecast.

Keywords: Forecasting, time series, short-term forecast, Internet.

1. Introduction

The Internet Services Unit (ISU) is a department of King Abdulaziz City for Science and Technology (KACST). It is responsible for providing Internet services in the Kingdom of Saudi Arabia (KSA) in cooperation with telecommunication providers from the private sector. The ISU was established in 1418 AH (1998 G). Its objective is to link academic, research, and some government agencies in Saudi Arabia to the Internet and provide high quality services[1].

Customer demand short-term forecasting is crucial for the Internet Service Provider (ISP) because it should help network engineers do a quick and proper load distribution in case of an upstream provider link failure. A simple short-term forecasting technique is needed, which is applied to all customers, in order to give a better demand visibility for the next half an hour. Distributing customers' load over upstream providers becomes more complicated when there are multiple cable failures and when the number of customers increases.

2. Statement of the Problem

The Internet Service Provider (ISP) pays for submarine Synchronous Transport Module (STM) cables with different capacities; STM-1 (155 Mbps), STM-4 (620 Mbps), STM-16 (2480 Mbps) and Ethernet (1 Gbps) links from upstream providers. Figure 1 shows the World's submarine cable map of 2016[2]. In this map, the darker color for a certain territory means a more resilient territory, where resiliency represents the territory ability to sustain submarine cable faults.

Internet services are supposed to be continuously provided to the clients 24 hours a day, seven days a week. However, there are times when the ISP faces problems in providing this service on a continuous basis especially when there are external interruptions. When such interruptions occur, the ISP personnel become under pressure to satisfy their clients, because they have to change their traffic “load distribution” configuration. If they do not change their load distribution configuration, their clients usually raise complaints because of low quality internet services. This problem is more critical since the ISP personnel do not know their clients’ demand beforehand.

Currently, customer demands (C_x) are distributed manually on upstream providers (P_x). It is one of the daily tasks for ISP personnel to monitor all the links and make sure that no traffic congestion occurs. All demand of a customer is preferred to be on a single upstream provider and backed up on another one. This is called “load distribution”. Figure 2(a) shows an example of load distribution. Filled squares represent upstream providers with cable direction either east (E) or west (W). The number at the bottom of every square represents the upstream provider capacity in Mbps. The filled circles represent links for current customer demand while empty circles represent links of a backup plan. The number at the bottom of every circle represents current customer demand in Mbps.

Customer demand short-term forecasting is crucial for the ISU because it should help network engineers do a quick and proper load distribution in case of an upstream provider link failure. A simple short-term forecasting technique is needed, which is applied to all customers, in order to give a better demand visibility for the next half an hour of Internet usage. Load distribution becomes more complicated when there are multiple cable failures and when the number of customers increases.

Figure 2(b) shows the backup plan in case of failure of cable (P_3) for the same example given in Figure 2a. Moreover, there is an over-utilization of 133% on the (P_4) link. A better distribution is obtained if customer (C_6) is moved to internet provider (P_2) and customer (C_9) to internet provider (P_5). This will change the utilization on (P_4) and (P_2) to be approximately 102%. Customers on over-utilized links will feel slowness due to lengthier queues and packet drops. It is important to note that utilization is changing with time according to customer’s actual demand that changes with time as well**.**

There are two causes of service interruptions, namely planned activities and unplanned activities. These interruptions could be the result of submarine cable cuts. Due to the widespread distribution of submarine cables, probability of unplanned service interruptions is considerably high. Various planned interruption activities might be overlapping with one another because submarine cables are maintained by different groups. This normally causes large losses in international capacities.

There are many causes for unplanned service interruptions such as the Mediterranean cable cuts reported by *Réseaux IP Européens* (RIPE) (see appendix A). It might be due to natural disasters such as tsunamis, earthquakes or volcanoes. Human intervention is another cause that constitutes the majority of these interruptions. An interruption could be either intentional or accidental. An example of intentional interruption is sabotage such as the one that happened in Libya, Darna on 28th of August 2013[3]. Accidental cable cuts are mostly caused by ships' anchors.

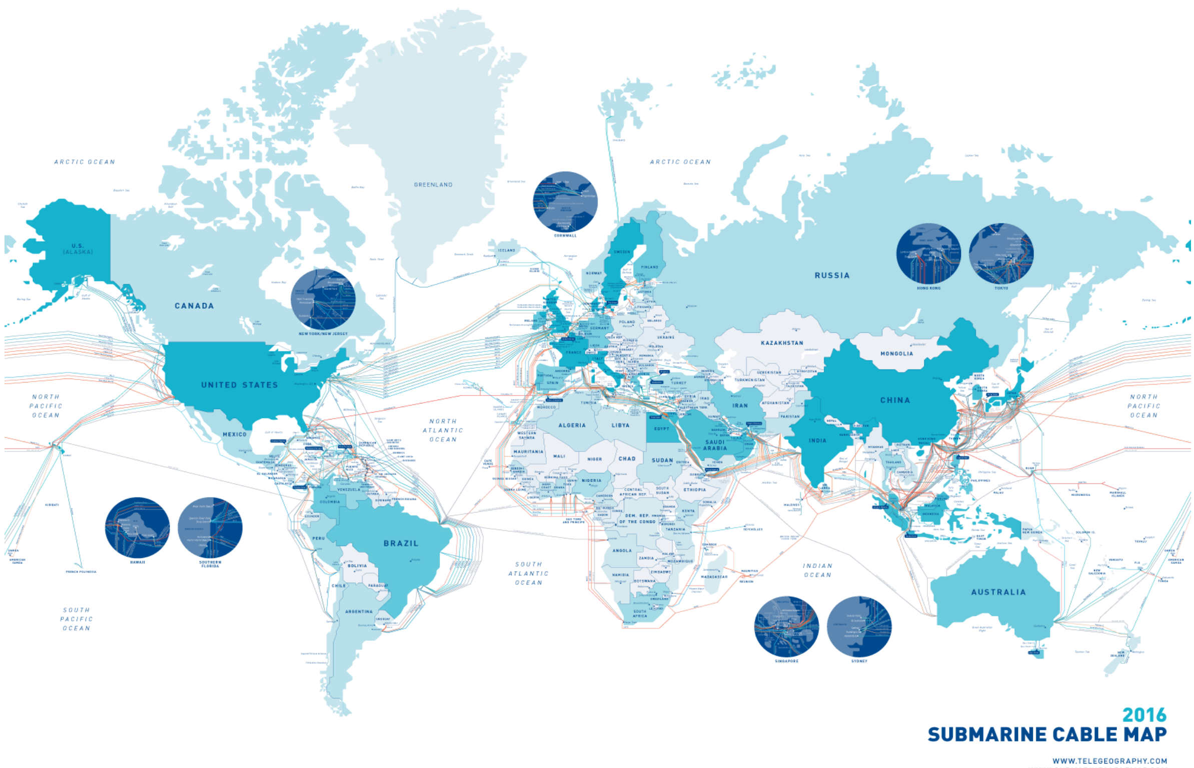

Fig. 1. 2016 Submarine Cables' Map (Source:www.telegeography.com) .

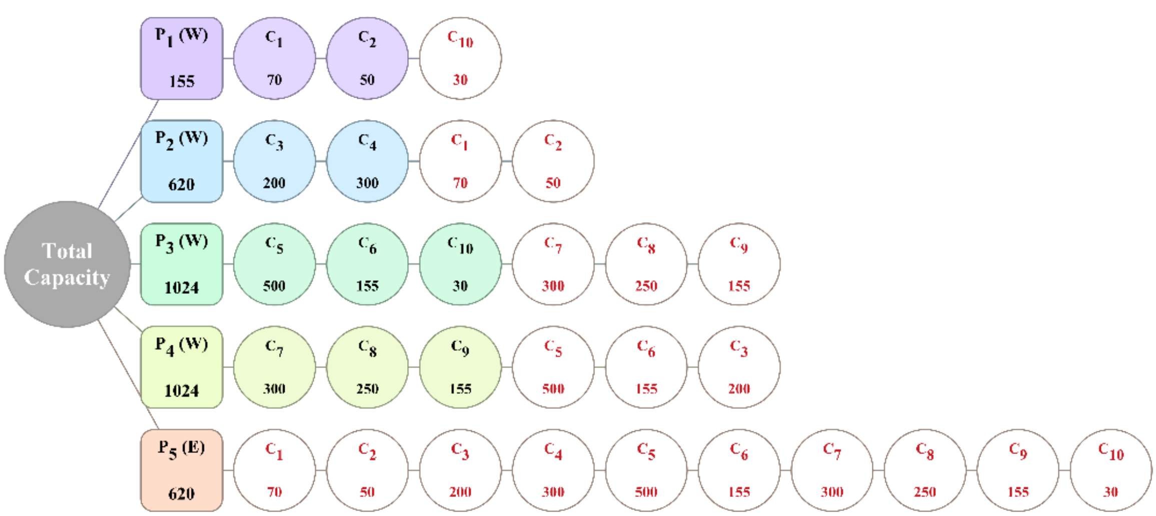

Fig. 2a. Example of Customers' Load Distribution.

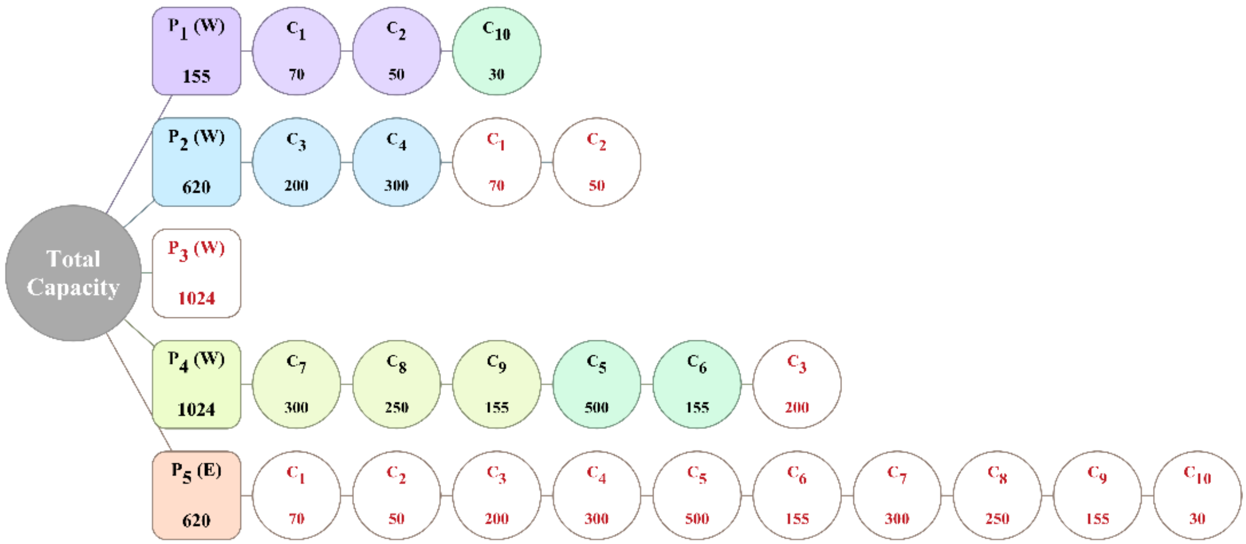

Fig. 2b. Example of Load Distribution in Case of a Cable Cut on P_3.

3. Research Goal

This research aims to partially alleviate the above stated problem by providing good forecasting of clients' demand. Thus, the goal is to investigate a number of short-term forecasting methods and select the best method for mitigating the problem.

4. Literature Review

Internet traffic prediction is very important for ISPs. A lot of research has been carried out to forecast the needed bandwidth. Different methods can be used to make long-term, medium-term or short-term forecasting. A lot of research is focused on long-term forecasting to do capacity planning. Alam (2007) worked on forecasting the demand of Pakistan's Internet backbone[4]. He used two-year data between two two-year nodes; Lahore and Karachi, using the Autoregressive Integrated Moving Average (ARIMA) method. His model resulted in 7% deviation from the actual demand values. In particular, the ARIMA time series model was found to be appropriate in modeling nonstationary data traffic[5][6], as well as in modeling time-varying telephone traffic[7]. Neural network techniques were used to provide a better long-term forecast as in Ahmed[8], Awduche et al.[9], and Gómez-Gil et al. [10].

A simple mid-term forecast was done for France Telecom IP international transit at a two-hour time scale for nineteen weeks[11]. The idea was to come up with a simple nonstandard model based on statistical tools such as the mean and the standard deviation to make a five-week prediction. The majority of link counts was found to have a median absolute relative error lying between 5% and 50%[11].

Short-term forecasting methods include naïve, moving averages, weighted moving averages, and exponential smoothing. These methods are discussed in many books such as those of Axater[12] and Fraser[13].

A short-term forecast was discussed by Cortez et al.[14] where several forecasting approaches were applied to TCP/IP traffic. These included three different Time Series Forecasting (TSF) methods: the Holt-Winters, the ARIMA methodology and a Neural Network Ensemble (NNE) approach. Recent data, collected from two large Internet Service

Providers (ISPs), were analyzed using different forecasting types (or scales): real-time (every five minutes) and short-term (hourly aggregated values). Furthermore, each method was tested under several forecasting horizons, from one to twenty-four periods ahead.

A remarkable observation made by Klevecka[15] is that in most cases the differences in quality between short-term forecasts of network traffic produced by complex models (such as ARIMA-like and neural networks) and linear models (namely exponential smoothing) are not statistically significant. Dort-golts[16] showed that a simple exponential smoothing with an adaptive smoothing parameter and an evaluation interval size about 10-15 points, operating on a highly averaged time series with 21-seconds time-step, can be recognized as the best prediction method in the whole set of methods of merit. The mean averaged percentage error proved to be near 20%, on the border dividing high and acceptable forecasting quality.

5. Methodology

We collected the bandwidth usage information for one of the most important clients of the ISU; King Abdulaziz University (KAU), inbound and outbound traffic. Data covered the period from 10/29/2014 00:00:00 to 11/12/2014 23:30:00. We got 720 points for inbound traffic, and 720 points for outbound traffic taken at 30-minute time intervals. Table B.1, in appendix B, shows a sample of KAU data that were collected.

Then, we compared four standard forecasting methods on the data to determine the most suitable method for ISU. Following is the list of the selected methods:

- Naïve Forecast.
- k-period Moving Average Forecast.
- k-period Weighted Moving Average Forecast.
- Exponential Smoothing Forecast.

In the following sections, we give a brief description about every method.

There are two types of forecast categories Qualitative forecast and Quantitative forecast. Qualitative forecast deals with customer behavior, surveys, etc. Quantitative forecast deals with time series methods and (associated) causal methods. Quantitative forecast is used in our short-term forecast. The most common forecast methods with time series models are the aforementioned four selected methods as well as the two methods of exponential smoothing with trend, and trend projection.

A time series forecast depends on past values. It assumes that facts influencing the past and present will continue their influence in the future. Next, we give a brief overview of the various forecasting techniques used in this research.

5.1. Naïve Method

Naïve forecast, also called *Last Value* forecasting method, is one of the simplest possible forecasts and has the following criteria that it

1. Is based on historical data of the previous day.
2. Assumes that the more recent time periods of data represent the best predictions or forecast for future results.
3. Does not take into account data trend, cyclical effects or seasonality.
4. Seems to work better with data that are reported on a daily or weekly basis.
5. Assumes tomorrow will be like today.

6. Ignores any historical data previous to that of today.
7. Assumes the traffic in the next period is the same as traffic in the most recent period.

The naïve forecasting method gives the forecast value for a given time period as the value for the previous time period:

$$F_t = X_{t-1}, \tag{1}$$

where

F_t: the forecast value for time period t,

X_{t-1}: the actual value for time period $t-1$.

5.2. Moving Average Method

The Moving Average method is also known as the arithmetic average method. Moving average forecasts are computed by averaging data for several time periods and using the average as the forecast for the next period. The most primary model of moving average models is the simple moving average model. This model calculates the forecast for time period t as the average of the values for a given number of previous time periods as shown in the following equation:

$$F_t = (X_{t-1} + X_{t-2} + X_{t-3} + \cdots + X_{t-n})/n\,, \tag{2}$$

The Moving Average forecast has the features that it

1. Is used in the case of little or no trend, seasonal, and cyclical patterns.
2. Smoothes the data to form a trend following indicator.
3. Does not predict direction.
4. Defines the current direction with a lag.
5. Is, in simple form, the most popular technical tool used by traders.
6. Is used mainly to identify trend direction.
7. Provides overall impression of data over time.

5.3. Weighted Moving Average Method

The Weighted moving average method is used when trend is present. Older data are usually less important than more recent data, and hence they are given less weight. Weighted moving average forecast provides more responsiveness to simple moving average forecast when there is a trend in the data. The formula used is

$$M = \left(\sum_{t=1}^{n} W_t \times V_t\right) \Big/ \left(\sum_{t=1}^{n} W_t\right), \tag{3}$$

where

M: Average value,

V_t: Actual value, at instance t,

W_t: Weighting factor, at instance t,

n: Number of periods in the weighting group.

Some of the disadvantages of moving averages are that they.

1. Require much more historical data,
2. Are difficult to trace seasonal and cyclical pattern,
3. Do not forecast well due to the delay between actual outcome and forecast,
4. Are sometimes outperformed by weighted MA.

5.4. Exponential Smoothing Method

The Exponential Smoothing Method is a special case of weighted moving average. Most recent data are weighted most, and weights decline exponentially. The method requires a smoothing constant (α), which ranges (exclusively) from 0 to 1. Increasing (α) makes the forecast less sensitive. The exponential smoothing method is used most effectively to forecast demand for data which exhibits a slow varying trend. This method uses the formula:

$$F_{t+1} = \alpha X_t + (1 - \alpha)F_t, \tag{4}$$

where $(0 < \alpha < 1)$. The present forecast is a weighted sum of the last data value X_t and the preceding forecast F_t for the period that just ended. The exponential smoothing average method reacts more quickly than the moving average. One of the drawbacks of the exponential smoothing average is that it lags behind a continuing trend. Another disadvantage is that it is difficult to choose an appropriate smoothing constant. If α is chosen to be small, response to change will be slow, and that will result in a smooth forecast. On the other hand, if α is chosen to be large, the response to change will be faster. This will result in more variance in the forecast.

By visual inspection of our data, we observe the existence of four different clusters, to which we split the data as follows

1. Week-days inbound (WD_IN) traffic.
2. Week-days outbound (WD_OUT) traffic.
3. Week-ends inbound (WE_IN) traffic.
4. Week-ends outbound (WE_OUT) traffic.

Forecasting techniques with selected parameters were as follows:

5. Naïve forecast (Naïve)
6. Exponential Smoothing with $\alpha = 0.3$ (EXP(0.3))
7. Exponential Smoothing with $\alpha = 0.6$ (EXP(0.6))
8. Exponential Smoothing with $\alpha = 0.9$ (EXP(0.9))
9. 2-DayMoving Average (2MA)
10. 2-Day Weighted Moving Average (2WMA)
11. 3-Day Moving Average (3MA)
12. 3-Day Weighted Moving Average (3WMA)
13. 4-Day Moving Average (4MA)
14. 4-Day Weighted Moving Average (4WMA)
15. 5-Day Moving Average (5MA)
16. 5-Day Weighted Moving Average (5WMA)

6. Results

Figures 3-6 show a one day forecast for each of the aforementioned four cluster types. Each of these figures is split into two figures: a figure (a) presenting full history of the data, and another figure (b) which is a replication of the (a) figure but with a limited history of the data and, (correspondingly), and expanded time axis. For each of the figures, results of prediction start to appear (along with actual data at the time point $t = 529$ for week-days and $t = 193$ for week-ends in units of 30 minutes. Figures 3-6 visually indicate various prediction methods have wide variability in their tracking of the actual data. However, it is somehow difficult to rank these methods visually as to their various degrees of success in making correct predictions. We delegate the task of ranking the used methods to the following section in which we abandon visual pictorial plots to use their corresponding numerical values.

7. Discussion

In this section we discuss how we differentiate between the various forecasting methods used. Also, we note the effect of visual clustering we did on our data. We will focus on the error analysis of the different forecasting methods. Tables 1 to 4 show the various error analysis results. Each of these tables makes use of three numerical results defined as follows

$$Mean\ Absolute\ Deviation\ (MAD) = \sum_{t=1}^{n} |X_t - F_t| \Big/ n, \quad (5)$$

$$Mean\ Square\ Error\ (MSE) = \sum_{t=1}^{n} (X_t - F_t)^2 \Big/ n, \quad (6)$$

$$Mean\ Absolute\ Percent\ Error\ (MAPE = \frac{100}{n} \times \sum_{t=1}^{n} |X_t - F_t|, \quad (7)$$

From the tables 1 to 4, we see that the most preferable method is **Exponential Smoothing with $\boldsymbol{\alpha = 0.3}$** for most of the forecasting methods. There are four exceptions discussed in the following three points.

(1)MAD suggests 3WMA as the best, with minimum aggregate error, for the WD_IN cluster. However, the difference between the MAD error of 6.33E+08 (for 3WMA) and 6.34E+08 (for EXP(0.3)) is so small to the point that we can consider the two methods as equally preferable.

(2)MAPE suggests 5MA as the best, with minimum aggregate error, for both WD_IN and WD_OUT clusters. However the differences with the EXP(0.3) method are not so big. Hence, using the EXP(0.3) method seems to be quite acceptable.

(3)Finally, MAPE also suggests that 3WMA is the best, with the minimum error, for the WE_OUT cluster. However, by striving for one unified method and supported by the small size of the sample, we are going with the Exponential Smoothing method with α= 0.3.

In this paper, we compared several forecasting methods for inbound/outbound weekdays/weekends Internet traffic provided for KAU for a specific interval of time. We conclude that in most cases the best forecasting method is that of exponential smoothing using a smoothing parameter α having value of 0.3.

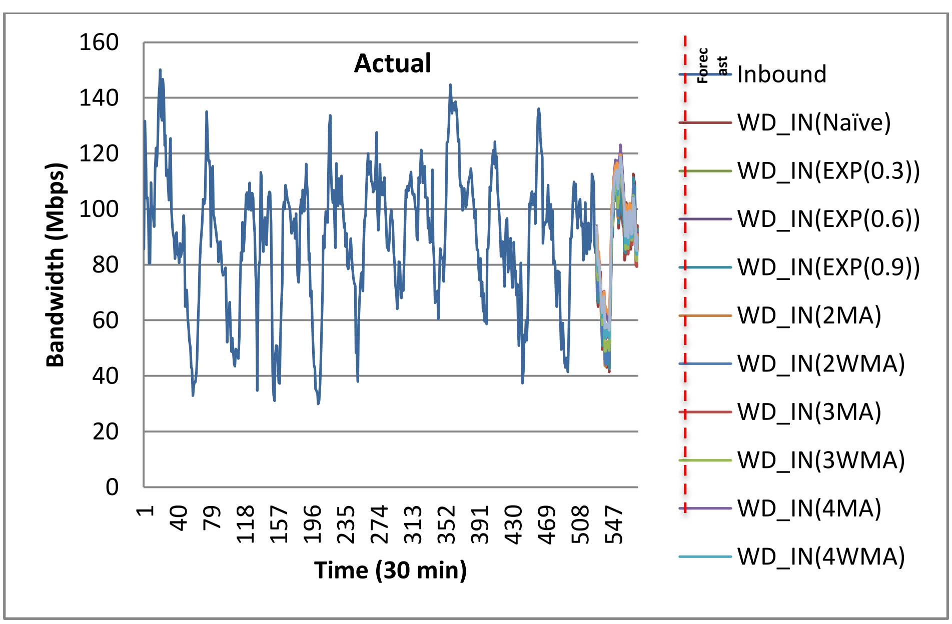

Fig. 3a. Week-days Inbound Actual and Forecast, (Full History).

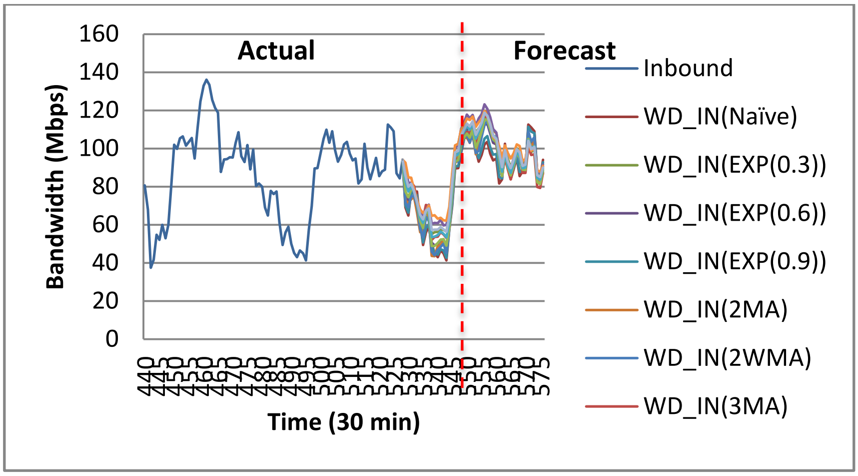

Fig. 3b. Week-days Inbound Actual and Forecast, (Limited History).

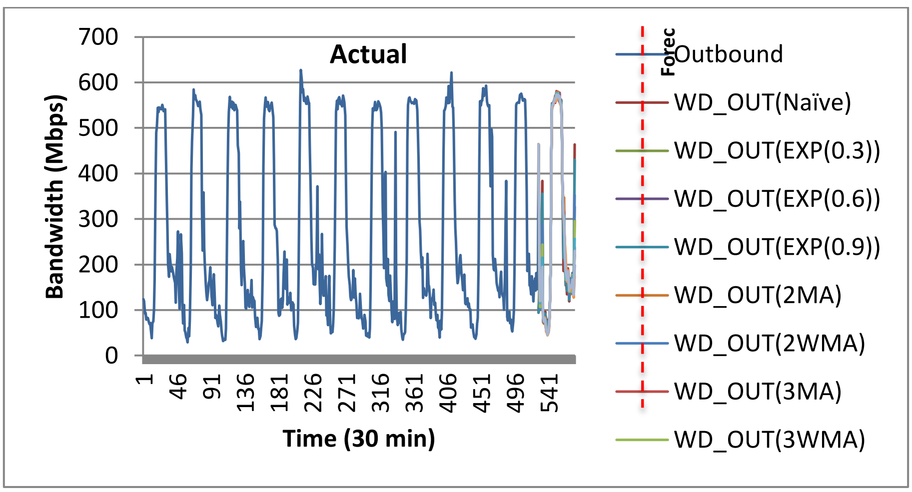

Fig. 4a. Week-days Outbound Actual and Forecast, (Full History).

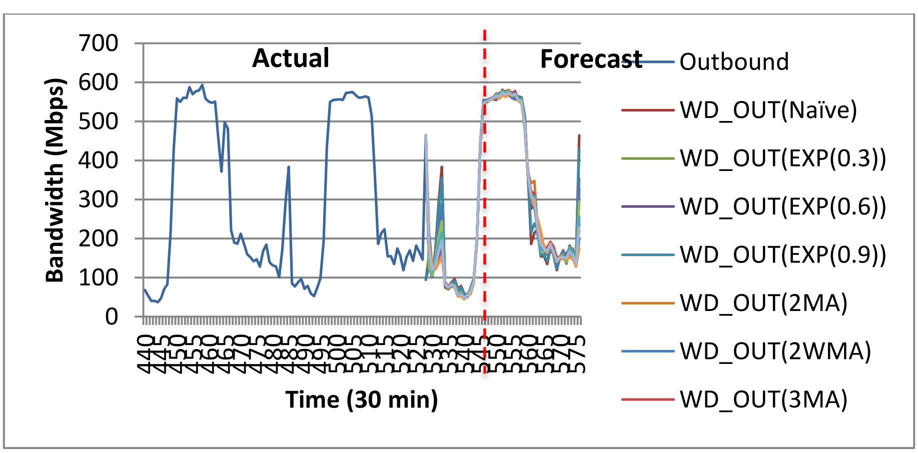

Fig. 4b. Week-days Outbound Actual and Forecast, (Limited History).

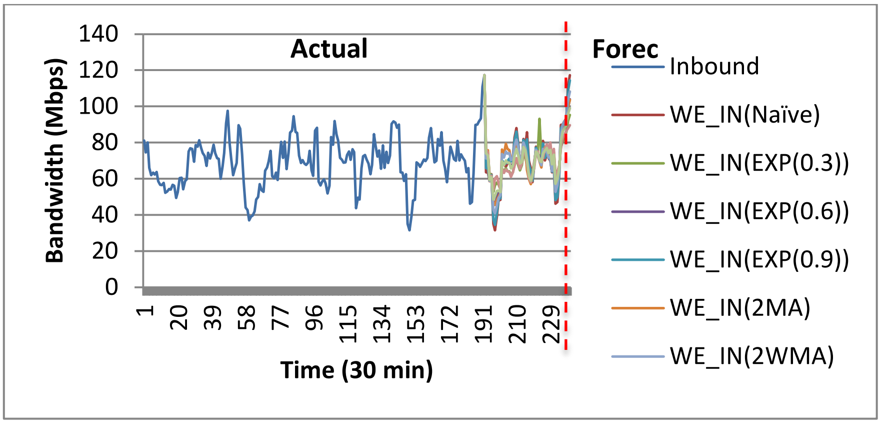

Fig. 5a. Week-ends Inbound Actual and Forecast, (Full History).

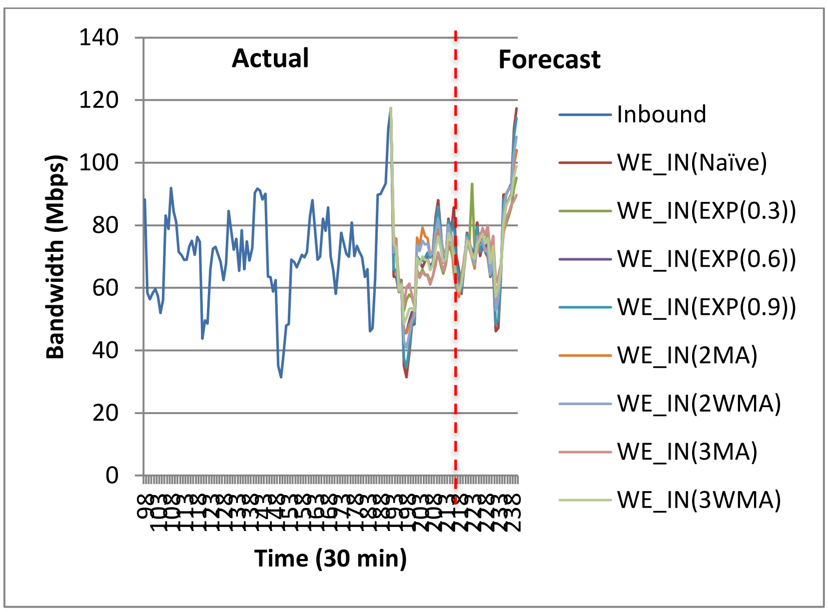

Fig. 5b. Week-ends Inbound Actual and Forecast, (Limited History).

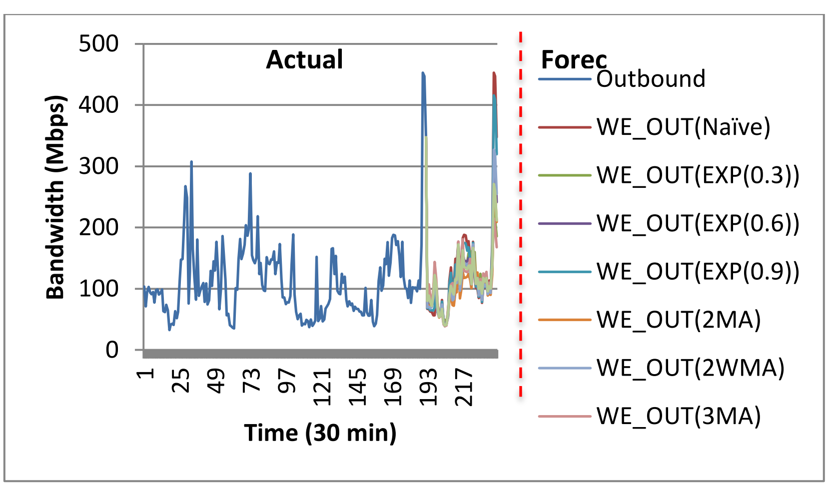

Fig. 6a. Week-ends Outbound Actual and Forecast, (Full History).

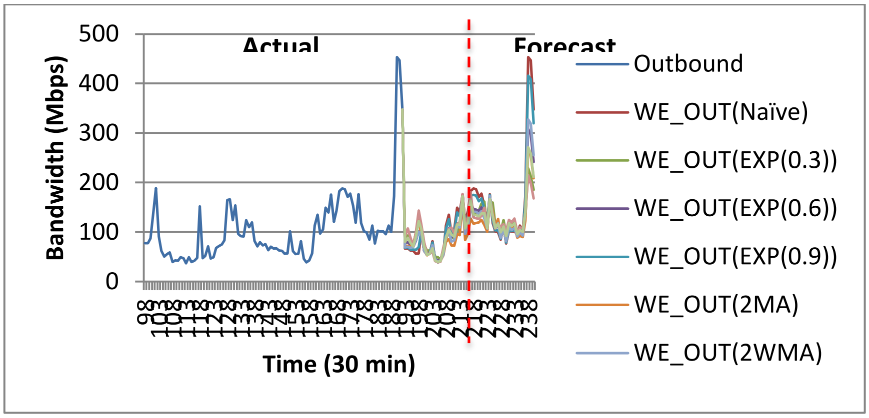

Fig. 6b. Week-ends Outbound Actual and Forecast, (Limited History).

Table 1. Week-days Inbound Traffic Error Analysis.

	MAD	MSE ($\times 10^9$)	MAPE%
Naïve	763392201.05	20990508.0	20.81
EXP(0.3)	633630970.44	**12227970.7**	17.68
EXP(0.6)	681464440.47	15025343.9	18.73
EXP(0.9)	731315760.45	19030147.1	19.89
2MA	673729830.71	14222423.0	17.67
2WMA	654266405.62	13394388.0	16.81
3MA	656569099.91	13251199.9	17.01
3WMA	**632659985.28**	12445370.1	16.07
4MA	680055367.87	13670603.9	17.62
4WMA	638006815.55	12431031.1	16.19
5MA	646883609.96	12913145.2	**15.71**
5WMA	644539257.75	12524084.9	15.80

Table 2. Week-days Outbound Traffic Error Analysis.

	MAD	MSE ($\times 10^9$)	MAPE%
Naïve	1872611784.50	206458905.0	24.29
EXP(0.3)	**1417564204.83**	**123083097.5**	18.50
EXP(0.6)	1581523812.07	149506255.6	20.65
EXP(0.9)	1786348883.38	188526173.7	23.18
2MA	1625202868.24	156298411.8	21.21
2WMA	1655039145.35	165440866.9	21.49
3MA	1580570149.85	148176688.1	19.84
3WMA	1581082164.09	153670431.4	19.77
4MA	1505819787.00	146344105.0	18.25
4WMA	1550380467.37	154136949.0	18.87
5MA	1466770574.36	149607619.6	**17.98**
5WMA	1509996727.94	153975428.5	18.88

Table 3. Week-ends Inbound Traffic Error Analysis.

	MAD	MSE ($\times 10^9$)	MAPE%
Naïve	613170737.99	13385269.5	19.36
EXP(0.3)	**528160278.90**	**9258313.8**	**17.16**
EXP(0.6)	570328923.18	11208530.5	18.35
EXP(0.9)	610457883.74	13258833.4	19.34
2MA	663375917.38	14208492.0	20.90
2WMA	645572717.33	14013281.0	20.23
3MA	669213643.50	13416587.0	22.46
3WMA	610275005.77	12219454.9	20.67

Table 4. Week-ends Outbound Traffic Error Analysis.

	MAD	MSE ($\times 10^9$)	MAPE%
Naïve	3090363185.65	380315069.2	65.65
EXP(0.3)	**2177598992.28**	**206464158.8**	46.22
EXP(0.6)	2538177515.75	279531017.4	51.37
EXP(0.9)	2933158435.89	348751773.3	61.91
2MA	2286609799.61	287213937.7	53.78
2WMA	2467483580.57	314174161.9	58.05
3MA	2368706319.11	377020331.0	35.21
3WMA	2408784053.56	40359579.4	**34.52**

8. Conclusions

Since $\alpha = 0.3$, and $\alpha = 0.6$ were selected as trial parameter values of the exponential smoothing method, and since $\alpha = 0.3$ was found to be the best, it is worth investigating other values for α that are close to 0.3, such as $\alpha = 0.2$ and $\alpha = 0.4$. This might lead to a better forecasting parameter. Other forecasting methods should also be investigated to improve the short-term forecast especially when the number of clients increases. Furthermore, similar analyses should be done for all clients in order to find out if one forecasting method could be used for all.

This work should help the KACST ISU, as a service provider, to do better load distribution between international links. Also, this work can help in approving *down times* and *maintenance windows* requested by cable providers. Therefore it will enhance the international links fault tolerance. Moreover, it will help in detecting cyber security attacks or SPAM by showing irregularity in traffic behavior. Finally, this work should hopefully reduce clients' complaints and improve the quality of service for them.

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Appendix A

Mediterranean Fiber Cable Cut Reported by Réseaux IP Européens (RIPE)

Following is a list of Mediterranean fiber cable cuts reported by *Réseaux IP Européens* (RIPE)[17]:

• **Wednesday, 23 January 2008 (exact time unknown):** FALCON cable, segment 7b damaged (Arabian Gulf)[1]

Note: This is one week prior to the Mediterranean outrages.

• **Wednesday, 30 January 2008, 04:30 (UTC):** SEA-ME-WE-4 cable, segment 4/Alexandria-Marseille, 25 kilo-meters from Alexandria, Egypt.

• **Wednesday, 30 January 2008, 08:00 (UTC):** FLAG Europe-Asia cable (FEA), segment D (EG-IT) cut approximately 8.3 kilo-meters from Alexandria, Egypt.

• **Friday, 1 February 2008, 05:59 (UTC):** FALCON cable, segments 2 and 7a (AE-OM) cut approximately 56 kilo-meters from Dubai, UAE.

• **Friday, 1 February 2008 (exact time unknown):** Unidentified cable, between Halul (QA) and Das (UAE).

• **Friday, 8 February 2008 (exact time unknown):** SEA-ME-WE-4 repair completed.

• **Saturday, 9 February 2008, 18:00 (UTC):** FEA segment D repair completed.

• **Sunday, 10 February 2008, 10:00 (UTC):** FALCON cable repair completed.

• **Thursday, 14 February 2008:** Doha-Halul part of the unidentified QA-UAE cable "to be operational soon".

Appendix B

Sample OF KAU Collected Data

Table B.1: Sample of KAU collected data.

Date (mm/dd/yy)	Time (24hrs)	Inbound (bps)	Outbound (bps)
10/29/14	0:00	85654327.29	123799923.56
10/29/14	0:30	131609293.33	119782782.32
10/29/14	1:00	119283328.53	92362228.35
10/29/14	1:30	103869173.23	93848647.14
10/29/14	2:00	104137214.00	79283495.11
10/29/14	2:30	96560983.04	83326737.88
10/29/14	3:00	80570318.31	82689191.91
10/29/14	3:30	80515424.92	73214448.97
10/29/14	4:00	109519077.95	69086177.48
10/29/14	4:30	101246117.68	72195675.66
10/29/14	5:00	100691556.45	51836173.42
10/29/14	5:30	96154712.09	38467145.37
10/29/14	6:00	93674902.40	71206880.06
10/29/14	6:30	114249041.10	75193581.45
10/29/14	7:00	121975783.08	100326120.43
10/29/14	7:30	115577818.73	167404219.37
10/29/14	8:00	123519904.24	380173779.91
10/29/14	8:30	139235773.11	489815614.45
10/29/14	9:00	144701633.24	502450762.56

[1] Originally inadvertently written (Persian Gulf)

التنبؤ قصير الأجل بواسطة السلاسل الزمنية لحركة المرور في شبكة الشبكات (الإنترنت)

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المستخلص. يتوقع من مقدمي خدمة شبكة الشبكات (الإنترنت) أن يقوموا بتزويد خدماتهم لجميع العملاء على مدار الساعة دون انقطاع. إلا أن التخطيط لهذا النشاط يتطلب عددا من المهام (مثل التنبؤ بطلب العملاء) التي يجب أخذها بعين الاعتبار للوفاء بأهداف العمل لا سيما في مواجهة الكوارث. تعرض هذه الورقة نتائج استخدام أربع طرائق للتنبؤ بالطلب من عميل واحد عند مزودٍ لخدمة شبكة الشبكات (الإنترنت). تم استخدام ما مجموعه ١٤٤٠ نقطة من نقاط استخدام عرض النطاق الترددي في حركة المرور المتجه للداخل والمتجه للخارج والتي أُخِذت كل ٣٠ دقيقة لمدة أسبوعين. ثم بعد تصنيف حركة المرور بصرياً وباستخدام قيم معالم مختلفة لطرق التنبؤ، تم دراسة ما مجموعه ٤٠ سلسلة زمنية مختلفة. نتائج الدراسة تشير إلى أن أفضل طريقة للتنبؤ على المدى القصير كانت طريقة التجانس الأسي مع استخدام مَعْلَمَة للتنعيم α قيمتها 0.3. إن نتائج هذه الدراسة ستكون عونا كبيرا لمزود الخدمة في شبكة الشبكات وذلك بمساعدته في تحديد أفضل خطة لتوزيع الحمل بين الروابط الدولية وكذلك المساعدة في تقديم الموافقة على أوقات انقطاع الخدمة ونوافذ الصيانة التي يتقدم بها مزودو خدمات الكابلات. وهذه النتائج من شأنها أن تساعد أيضا في الكشف عن بعض أنواع هجمات الأمن الفضائي أو البريد المزعج وتقليل شكاوى العملاء، وبالتالي تحسين جودة خدمتهم. وكعمل مستقبلي، نوصي باستخدام قيم متقاربة من مَعْلَمَة التنعيم بهدف تحسين التوقعات.

الكلمات المفتاحية: التنبؤ، السلاسل الزمنية، التنبؤ قصير الأجل، شبكة الشبكات.