Internet Traffic Volumes Characterization and Forecasting

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May 2016

ABSTRACT

Internet usage increases every year and the need to estimate the growth of the generated traffic has become a major topic. Forecasting actual figures in advance is essential for bandwidth allocation, networking design and investment planning. In this thesis novel mathematical equations are presented to model and to predict long-term Internet traffic in terms of total aggregating volume, globally and more locally. Historical traffic data from consecutive years have revealed hidden numerical patterns as the values progress year over year and this trend can be well represented with appropriate mathematical relations. The proposed formulae have excellent fitting properties over long-history measurements and can indicate forthcoming traffic for the next years with an exceptionally low prediction error. In cases where pending traffic data have already become available, the suggested equations provide more successful results than the respective projections that come from worldwide leading research. The studies also imply that future traffic strongly depends on the past activity and on the growth of Internet users, provided that a big and representative sample of pertinent data exists from large geographical areas. To the best of my knowledge this work is the first to introduce effective prediction methods that exclusively rely on the static attributes and the progression properties of historical values.

DEDICATION

I dedicate this thesis to all Scientists of all time who have made great discoveries and have contributed to the advancement of human civilization.

ACKNOWLEDGEMENTS

I gratefully thank my supervisor for his intense support to deal with my personal and studying difficulties I have faced during my research studies.

I would also like to thank my sponsor, the Scottish Informatics and Computer Science Alliance (SICSA), and my University for their funding support the last three and a half years. Without this scholarship, these studies would have been impossible.

Last but not least I thank Iain McCrone, Christine McBride and Claire Porter, members of administrative staff.

ACADEMIC REGISTRY
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GLOSSARY

AARIMA	Adjusted ARIMA
AGR	Annual Growth Rate
ANN	Artificial Neural Network
ARCH	Auto Regressive Conditional Heteroscedasticity
ARE	Average Relative Error (sometimes also noted as Absolute)
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
AS	Autonomous System
BS	Base Station
CAGR	Compound Annual Growth Rate
CAIDA	Centre for Applied Internet Data Analysis
CDF	Cumulative Distribution Function
CDMA	Code Division Multiple Access
CLT	Central Limit Theorem
CSMA/CA	Carrier Sensing Multiple Access with Collision Avoidance
DE-CIX	Deutscher Commercial Internet Exchange
DTN	Delay Tolerant Network
EB	Exabyte
FARIMA	Fractional Auto Regressive Integrated Moving Average
GARCH	Generalized Auto Regressive Conditional Heteroscedasticity
GigE	Gigabit Ethernet
GDP	Gross Domestic Product
HAPrE	Historical Average Prediction Error
HMM	Hidden Markov Model
IP	Internet Protocol
IPTV	Internet Protocol Television
ISDN	Integrated Services Digital Network
ISP	Internet Service Provider
IT	Information Technology
ITU	International Telecommunications Unit
IXP	Internet Exchange Point
LAN	Local Area Network
LINX	London Internet Exchange
LRD	Long Range Dependence
LTF	Long Term Forecasting
MAE	Mean Absolute Error

MAPE	Mean Absolute Percentage Error
MINTS	Minnesota of Internet Traffic Studies
MMPP	Markov Modulated Poisson Process
MSE	Mean Square Error
MTU	Maximum Transmission Unit
NN	Neural Network
NNE	Neural Network Ensemble
NTF	Near Term Forecasting
OC	Optical Carrier
P2P	Peer-to-Peer
PB	Petabyte
PoP	Point of Presence
PrE	Prediction Error
QNM	Queueing Network Model
QoS	Quality of Service
RWNN	Recurrent Wavelet Neural Network
RMSE	Root Mean Square Error
SARIMA	Seasonal ARIMA
SICSA	Scottish Informatics and Computer Science Alliance
SNMP	Simple Network Management Protocol
SRD	Short Range Dependence
STF	Short Term Forecasting
SVR	Support Vector Regression
TB	Terabyte
TCP	Transmission Control Protocol
TSD	Time Series Data
TSF	Time Series Forecasting
TUR	Traffic to Users Ratio
UDP	User Datagram Protocol
VBR	Variable Bit-Rate
VNI	Virtual Networking Index
WAN	Wide Area Network
WWW	World Wide Web

LIST OF PUBLICATIONS

1. Vlachos, N.K., King, P.J.B. "Global Internet Traffic Volume Prediction: Towards the Discovery of a New Formula". American Journal of Advanced Computing. AST Publishers, July 2015. Volume 2, Issue 3, pp. 71-84.

2. Vlachos, N.K., King, P.J.B. “Internet Traffic Classification and Features: Current Levels and Future Projections”. The 14th Annual Symposium on Convergence of Networking, Broadcasting and Telecommunications. PGNet 2013. pp. 224-227.

3. Vlachos, N.K., King, P.J.B. “Statistical Properties of Internet Traffic on a Personal, Local and Wide Area Network Level”. The 14th Annual Symposium on Convergence of Networking, Broadcasting and Telecommunications. PGNet 2013. pp. 202-207.

CHAPTER 1

Introduction

"If we knew what it was we were doing, it would not be called research, would it?"

- Albert Einstein

This chapter describes a brief historical view of the main existing literature, some important achievements and its connection with the present studies. Reasons for motivation and potential contribution in furtherance of established models are also highlighted.

1.1 Overview

The Internet is one of the most complex technology infrastructures of modern civilization. Defined as a network of networks [Rfc1122], the Internet has been generally increasing every year in terms of usage and geographical range since the early days of its development [Mar2014]. Latest technology advances along with the global population growth have resulted in more bandwidth and access speed. Thus, the communication equipment and underlying technical issues for Internet Service Providers (ISPs) and backbones would have to be determined accordingly and, ideally, in advance. The total number of Internet users across the world increases every year [Iws2015], [Ils2015], [Stat2015], [ITU2015] and so does the aggregate traffic which they generate on a continent and on a global scale [Cis2013], [CisVNI], [Kor2013], [UoM1]. Therefore, modelling and predicting the growth aspects of Internet traffic is technically and economically important as well as challenging and has received wide attention from researchers mainly since the 1990s.

There are numerous different methods and approaches that have been applied in order to characterize traffic in a variety of applications in short time intervals, on a medium time scale and up to the long horizon. One of the most important achievements in traffic modelling ever came from Leland et al in 1994 [Lel1994], in which the authors have clearly demonstrated that Ethernet Local Area Network (LAN) traffic is statistically self-similar, its bursty characteristics and the impact this would have on network behaviour. On this basis, sophisticated models have been also proposed to support the B type ISDN (Integrated Services Digital Network) deployment at that time [Lel1994]. Proceeding to the more recent days, another example of successful characterization of Internet traffic, but in terms of aggregating volume over several years, is presented by Korotky (2013) at Bell Laboratories, Alcatel-Lucent [Kor2013].

Similar to modelling, forecasting figures has also been a main topic and numerous studies have been conducted to project the traffic that we expect for the future. The associated timeframe varies according to the approach and the research method. It may range from a few minutes and extends up to several years but the investigations have a variety of techniques and many of them are usually different for near term estimations when compared to the long run. In any case, the majority of the studies have very good prediction results such as the in-depth work from Papagiannaki et al (2003 and 2005) to project traffic for at least six months ahead [Pap2003], [Pap2005] and from leading networking company Cisco Systems which focuses more on longer timeframes for traffic volumes forecasting [CisVNI], [Cis2014a]. On similar macroscopic horizons, the author in [Kor2013] familiarizes the audience with regression analysis on historical volume traffic data and demonstrates the excellent capabilities of his model to predict traffic.

In general, there are certain approaches that dominate the field of Internet traffic projections and which have been adopted by much of the relevant work for making traffic estimations. Historical measurements can be used to predict traffic on a networking link [Ber2009] but on a global scale too [Kor2013]. One of the most important and common approach is time series forecasting (TSF) by time series analysis, i.e. analysis of collected sequences of data points in the time domain. The methods used for this purpose vary depending on data type characteristics as well as the involved time intervals and the models can have many forms such as linear and non-linear. A widely used model to predict Internet traffic is the Auto Regressive Moving

Average (ARMA). This primitive model has a range of generalizations including the Auto Regressive Integrated Moving Average (ARIMA) and the Fractional Auto Regressive Integrated Moving Average (FARIMA). One of the scientists to popularize the ARMA model was George E.P. Box in 1970 [Box1970], one of the greatest statisticians of the twentieth century, and the method known as “Box-Jenkins” model has been used since then in time series forecasting. Non-linear models are also a strong tool for predictions; a good example is the Auto Regressive Conditional Heteroscedasticity (ARCH) and its extension Generalized Auto Regressive Conditional Heteroscedasticity (GARCH). The latter is not only a computer science reference model, e.g. in [Ana2008], but has also been successfully introduced in the field of econometrics in the twentieth century to predict certain aspects in economics [Bol1986]. In addition, neural networks (NNs) and artificial neural networks (ANNs) have been also proposed to forecast traffic figures and they combine good modelling characteristics and reasonable prediction results such as the studies described in [Wan2008] and [Mig2012] respectively.

However, apart from the aforementioned models, there are a number of further rigorous methods for modelling and forecasting of network behaviours and these tend to receive more attention in the last six years. Regression analysis, extrapolation and curve fitting are explicit examples of research in traffic characterization and future trends estimation. They are primarily based on recorded historical measurements mainly over long time periods from the past and some of them have prominent results in fitting historical trends and others operate with low prediction error.

1.2 Current Situation and Motivation

Forecasting Internet traffic is a fundamental concept in network provisioning and investing. The impact of traffic flow on networking configurations has technical and economic implications. In telecommunications, the planning usually accords with the long term trends and traffic predictions [Bab2006] and another important task is the precise and accurate measurements of the flow of Internet traffic generated from all connecting devices on a local and global scale [Vla2015]. The total mass of the global volume across the Internet increases on an annual basis and predicting forthcoming actual figures may be done a few to several years ahead. The aggregate traffic that crosses ISPs, major backbones and Internet exchange points (IXPs) is generally increasing and it is important that the software, hardware and equipment needs must be determined well ahead. Companies would need to estimate the amount of capitals to be invested and network administrators must identify the relevant technical issues. Therefore, it is essential that all necessary arrangements must be made prior to proceeding to network infrastructure design and machine set-ups. Predicting the flow of the actual information that is expected to cross a large district or the whole Internet will reduce the time and funds to be spent for design and equipment needs.

The hereby presented thesis investigates hidden numerical patterns in historical information over several years of traffic activity focusing on the aggregated traces of the total volumes rather than the more dynamic techniques of the popular methods, such as the ARMA, ARCH and NN models and their improvements. Capturing traffic data at certain locations can give a precise indication of the aggregated traffic volumes and future growth rates. In this way we are able to determine how much traffic we can expect in the next years and how this can influence the near and long term, macroscopic investments and network capacity planning. The measurements, nevertheless, may exclude some traffic that remains within a single service provider's network as well as traffic that is managed by private peering. This, in general, suggests that there is no way of a complete and accurate monitoring scheme of Internet traffic with absolutely precise figures and it is possible that this can result to considerable prediction errors. In other words, the diversity of traffic monitoring and the associated capturing techniques as well as the massive and distributed information that crosses the Internet would lead to imperfect measurements with an impact on future projections. But at the same time, a large and representative sample should give a good image of the future behaviour as long as the available data come from captured traces over large network areas. The initial hypothesis in a set of such pertinent data is to detect hidden relations over chronologically consecutive measurements and that those can be well characterized by proposed mathematical relations, which can indicate precise future figures. For instance in table 1, which is the largest available sample in terms of geographical range of Internet traffic volumes, there are certain properties in the numbers that appear in chronological order. The information in the table represents the global historical activity of Internet Protocol, wireline (fixed) and mobile traffic and it clearly shows that traffic increases in all categories as time progresses from the past on to the last year of which we have available information. Certain level of regression analysis and extensive experiments on detecting numerical properties have revealed that all captured aggregate traces encapsulate hidden patterns in their values in chronological order. Here, one of the main goals is to detect those patterns, fit them accordingly and produce a set of formulae which would characterize the history trend and then provide accurate projections on future values. Apart from the global Internet Protocol (IP) traffic, the same goal applies to much of the relevant historical measurements that are publicly available such as the Amsterdam Internet exchange (IXP) traffic details. Further material to be extensively used in these studies comes from Cisco's globally recorded measurements and from some important statistics for Internet users' growth. If market and user trends do not change significantly, the hereby proposed equations are expected to provide fairly accurate projections with an average associated prediction error of no more than 10% - but ideally less than 5% - for the next three to four years ahead. However, the prediction error is to be calculated as soon as the measurements we are expecting for the future become available on the Web.

Global Internet Traffic by Year	Traffic in Petabytes (PB) per Month		
	IP Traffic	*Fixed Internet Traffic*	*Mobile Internet Traffic*
2005	2,426	2,055	0.9
2006	3,992	3,339	4
2007	6,430	5,219	15
2008	9,927	7,639	38
2009	14,414	10,676	92
2010	20,197	14,929	256
2011	27,483	20,634	597
2012	-	31,338	885

Table 1: Historical volume data by three traffic types [Cis2013], [Wik2015a]

Due to the huge aggregated volumes on a global scale, the traffic is usually given in Petabytes per month (PB/month or PB/mo). PB is a multiple unit of Byte expressed as 1 PB = 10^{15} Bytes. However, because of the large distance between them, we usually relate the Petabyte to units at three orders of magnitude downwards, i.e. 1 PB = 10^3 Terabytes (TB). The latter is used to express aggregate traffic from sources that extend on a more local level rather than the massive global such as Internet exchange points.

In table 1, fixed and mobile traffic are part of the total IP and, according to forecast reports from Cisco Systems such as in [Cis2014a], the rest of the traffic refers to the managed IP part. If all three sub-categories are aggregated, the result equals to the overall IP traffic. Global volume is the totality of the traffic flow that has crossed the entire Internet. Since the early 1990s, the annual Internet Protocol traffic has been continuously increasing. However, numerical figures for respective annual growth indicate some level of decline in the last several years when we are to consider annual growth rate (AGR) figures. It is observed that the growth rate of the IP volumes in table 1 is decaying and this observation will be part of the investigation later in the core chapters. The totality of IP traffic is, without doubt, growing year over year but the pace of this growth has been observed to slow down. Computing respective AGRs means to divide the volume of a given year with the volume of the year before. If the rate is calculated at exactly 1 this means no change at all. A result, however, that has doubled (AGR = 2) indicates a volume as twice as much related to the previous year; if the AGR is found at less than 1 and greater than 0 this means that traffic levels have shrunk. In any case, however, the captured measurements must be complete without data loss or inaccuracies in order to proceed to further studies and precise estimations.

Certainly, the process of aggregating Internet traffic traces on a global – even on a local – scale is a difficult and time consuming task. The accuracy of the collected information of a specific network at one location is unlikely to be exactly the same with the measurements taken at another place, for the same network. In chapters 5 and 6 investigated is the totality of global IP traffic and its progression characteristics rather than the traffic generated only by wireline (fixed) devices or by mobile users. The main reason is because the flows that are generated merely by mobile or fixed data are just part of the total global IP traffic and only the latter crosses the global hardware infrastructure as a whole. However, some advice for further investigation on the mobile part is given in the concluding chapter. Another important fact that must be mentioned is that it seems there is only one main source of measurements conducted and captured for the global IP data and they come from Cisco Systems. This is convenient in the way that a second historical set would probably be different but at the same time it can be an evidence of how difficult is to measure Internet traffic. Similarly, the statistics on mobile traffic come from the same source as well and are available from 2005. Before that year, the information and data collections on the mobile traffic category were probably insufficient and may had not been extensively modelled. Later, however, it is observed that the overall mobile growth follows a similar trend to the rest of the traffic, even though the mobile characteristics seem to increase at a higher growth rate when compared to the fixed and the IP flow. To this end, all the information in table 1 evidences the constant increase of the Internet but at the same time there is not much research on the implications of volume growth and the potential hidden privileges and properties behind the numbers. The needs of the fast growing Internet market and the rapidly increasing number of users pose many challenges and support the scope for further research. The following questions are therefore proposed and must be accordingly addressed:

(i) Is there any numerical pattern in available consecutive historical measurements (for instance in table 1) to reveal some mathematical relation that is able to predict future traffic? If yes, is it exponential, linear or of some other algebraic form?

(ii) If a promising equation can be proposed, is it the same for every geographical scale of measurements and predictions or does it slightly/significantly vary?

(iii) How much level of dependence on the past can be assigned from the information and the variables of the produced formula(e) from (i) and (ii) above? In other words, is the forthcoming traffic indeed related to the past traffic activity and how strong is this dependence?

(iv) How much information of the past must be used to maximize traffic predictability in the long term?

(v) How is global Internet traffic growth related to the global Internet users? Is there a relation for this growth too?

All issues (i) to (v) are fully investigated, analysed and answered in detail in this thesis. Certain mathematical equations are produced with very good fitting results and very good prediction attempts so far on traffic volumes. There is not much research effort to address those problems and the present studies can be the beginning of a new era to indicate Internet traffic evolution. Furthermore, proposing algebraic equations to estimate future aggregate volumes is a strong scientific tool. Well-known mathematical relations are available for solving problems in all sciences: they are practical, straight-forward and easy to use by everyone who possesses only the basics in their area. The present topic is a good opportunity to expand knowledge and establish more directions to traffic modelling and forecasting. But, at the same time, how much work has been done by others to address questions (i) to (v) and whose approach is similar to this thesis but different from popular time series models such as the Auto-Regressive and the Moving Average?

1.3 Introducing Non-Dynamic Models

In these studies, the term “non-dynamic” or “static” is used. It refers to the methods that rely on long term historical measurements that cannot be altered or repeated, from which available figures will be used for modelling and forecasting. Static techniques are probably not suitable for capturing the detailed characteristics of traffic such as burstiness and self-similarity, but they are appropriate for describing trends and predicting future figures based on regression analysis, curve fitting, interpolation, extrapolation and pattern detection. The investigation is also to indicate the degree of influence that long term traffic has over the past corresponding traffic. A considerable amount of related work using pioneering static-based techniques has been adopted by other scientific fields as well for the purpose of short term and macroscopic predictions, including certain subjects in economics, computational biology and airport traffic. In the field of Internet studies, even though such techniques could have been properly involved, it seems that extensive research came on the surface only by the end of last decade. Specifically in 2009, a different view of studies in the area of Internet traffic characterization has started to gain considerable attention when the University of Minnesota publicised how much traffic there is on the Internet in terms of volumes and for different regions across the globe. In particular, the Minnesota of Internet Traffic Studies (MINTS) released statistics and facts about the real nature of Internet exchange points (IXPs), their growth and some traffic estimates for the US and the world by the end of 2009 [UoM1], [UoM2]. In brief, their prediction for 2009’s traffic growth has been calculated at approximately 1.5 in relation to 2008, for both the States and globally. Moreover, there are volume statistics for traffic sources from one hundred traffic sources portrayed in precise numbers, most of which are data coming from major IXPs reporting incoming and outgoing traffic, peak flows and the associated historical timeframe of the acquired traces. Much of this information comes from past traffic behaviour from several consecutive years, e.g. from 2005 or earlier up to January 2009, and all data all plotted on a X-Y axis co-ordinate system which clearly shows that trends can be characterized using fitting techniques and appropriate mathematical relations. Prediction attempts by employing this model are realistic. Some of the main outcomes of MINTS long time effort can be summarised as:

(i) Fitting available traffic data from historical activity tends to be a curve with some level of dispersion.

(ii) The historical trend of the aggregated IXP traffic can be well represented with appropriate exponential equations.

The growth rate of the traffic sources and the Internet exchange points that have been observed are obtained by regression analysis and their methodology is to "look for an exponential fit" of the following form [UoM3]:

$$y = 10^{bx + d} \tag{1}$$

Variable y is the volume and is expressed as a function of x, where x is the day on the X-axis. In the research conducted in this thesis, the methodology is similar to the MINTS except that the new proposed equations are produced with experimental pattern detection and are expressed as a function of ε, where ε refers to the year, rather than the day x in equation (1). The following graph and the information in table 2 include findings of the MINTS studies on curve fitting and details of the produced equations for the Amsterdam Internet exchange point, one of the largest and fastest growing IXPs in the world.

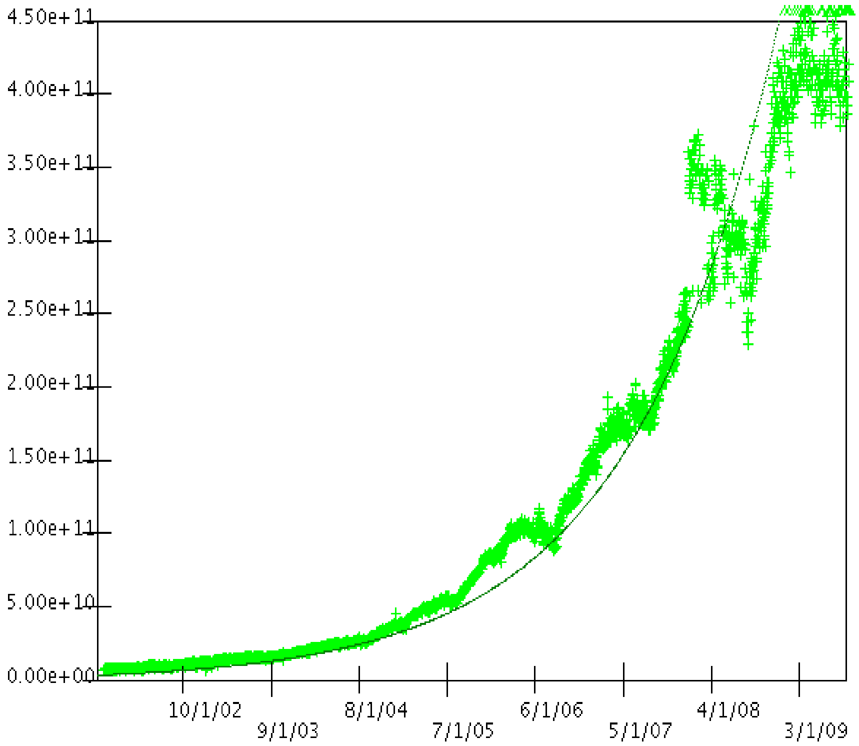


Figure 1: Incoming traffic volume (green) in bits/s and corresponding fitting curve for the Amsterdam IXP [UoM4]

Link Name	Current Link Stats	Average Traffic	Final Traffic	Annual Growth Rate	Start (MM-DD-YYYY)	Stop (MM-DD-YYYY)
Amsterdam Internet Exchange	URL	5.464e+10	7.114e+11	1.932	11-7-2001	8-22-2009

Incoming Equation	y = 10^(0.5069) * 10^(0.0008x)
Incoming Decimal Log Fit Equation	log(y) = 0.5069 + 0.000784x
Incoming Annual Growth Rate	1.9320
Outgoing Equation	y = 10^(0.5174) * 10^(0.0008x)
Outgoing Decimal Log Fit Equation	log(y) = 0.5174 + 0.000782x
Outgoing Annual Growth Rate	1.9289

Table 2: Produced equations details for the Amsterdam IXP for the data of figure 1 [UoM4]

However, according to their website, MINTS have conducted no further research since 2009 and most of the pages that contain those high-level studies have been last updated that same year. This work is one of the greatest efforts in modern traffic modelling and their novel approach of traffic data analysis was unique at that time and there was probably no other study with the same level of achievements using similar methods by 2009. It would be highly beneficial that we see further studies like this from other people who would give more knowledge to the static-adaptive ways of approaching Internet traffic modelling and forecasting.

Evidently, it can be observed that the total volume of the traffic sources coming from MINTS research efforts is growing and this is happening at a rate of more or less equal to the total volume in the entire world. However, a more important observation is that this growth is constantly slowing down on an annual basis and the same trend continues until this very day. The mean annual growth rate (AGR) for all analyzed 100 sites as studied by the MINTS has been calculated at 1.511 for period 2002-2009 [UoM2] and today this rate has decayed down to approximately 1.35. This means Internet traffic is (still) increasing as a whole but in terms of growth the latter calculations confirm a slight but progressive drop-down when we are to compare the variation rates of consecutive annual growth. This subject is extensively investigated in respective chapters.

Another great and rigorous effort in traffic characterization and forecasting is presented in a report from Bell Labs Technical Journal by Korotky (2013). The author performs linear regression analysis on global historical data for fixed Internet traffic available from company Cisco, to project aggregate volumes until 2020 using a "semi-empirical hyperbolic Compound Annual Growth Rate (CAGR) function" [Kor2013]. The model is an excellent representation not only for the history traffic but it also fits the near term forecasts up to 2016 (figure 2). Curve fitted projections to 2020 based on CAGR and proposed equations are further presented; they are discussed in the literature review and relevant chapters.

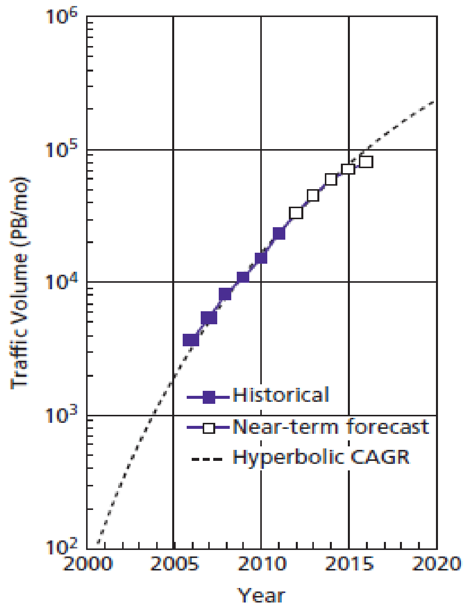


Figure 2: Regression analysis results for global fixed data demonstrates excellent fitting [Kor2013]

Another major and unique contribution to predictions on a variety of Internet traffic subjects comes from one of the leading networking companies, Cisco Systems. It is one of the main sources for near (NTF) and long term forecasting (LTF) not only in global and regional traffic, but also in a larger number of related categories, e.g. number of users and devices, access speeds, network connection and wireless technologies. An overview of their long time effort can be viewed in [CisVNIb] as well as in all detailed analyses through the next chapters. Cisco publicize a wide range of available measurements on their website and projections on frequently revised white paper reports, including the global volumes in table 1. However, their main approach to make predictions seems to be totally different than the other two techniques mentioned in this section, as they claim they rely on research from other companies and on a variety of analysis methods [CisVNIqa1]. In terms of how accurate their predictions are, the answer could be reasonable accurate and sometimes very good but at the same time they "have been characterized as conservative by some industry analysts and academicians" [CisVNIqa2]. Their future traffic estimates is a main subject in this thesis and are presented in depth.

1.4 Contribution of this Work

Predicting facts before they actually happen is a difficult task with certain pitfalls. Therefore estimations always accommodate error rates, some of which tend to be excessive, especially if the timeframe has been set to more than three years as this will be demonstrated in chapters that follow. However, the present studies aim to introduce techniques to achieve very low forecasting error percentages as soon as these are compared with the actual traffic figures once the latter are released. Proposed are mathematical formulae to characterize and estimate the nature of the traffic growth and project total volume flow as precisely as possible. The format of the suggested mathematical formulae include the year which we want to predict the traffic for and of equal importance is that all expressions can be revised with minimum effort. Historical traffic volumes have been analysed over consecutive chronological intervals from different traffic sources as outlined herein and a set of relations is introduced to project traffic data in the next three to four years, based on:

(i) The arithmetic relations of all values that can form explicit patterns coming from careful observations on all history measurements.

(ii) The fitting and progression characteristics of the actual time series data points.

Extensive analysis to extract hidden relations is performed on the actual historical figures based on the pattern scheme from (i) and how this trend is estimated to continue according to numerical experiments carried out in (ii). Then, appropriate variables and constants will be added to form the necessary equations and further numerical experiments are to select only those values that have optimum fitting results, i.e. the values calculated at the smallest error rate at the fitting stage. As a consequence, most of the fitting procedures have generally very low errors and this suggests successful estimates at the prediction stages for the available Internet traffic sources. Where already actual measurements have become available, the results are exceptional and it is expected that all proposed relations are to continue in the same line. The target is set to achieve prediction errors of less than 10% but the ideal situation would have values averaging below 5%. The latter percentage is indeed the case in most of the prediction evaluations, where available data are compared with the initial projections. The ideal forecasting error rate of less than 5% has been achieved with most of the proposed equations when those are evaluated against the real data that have become available. For the rest of the measurements however, that are not available yet, coming up with prediction error at more than 10% should not be totally excluded, considering:

(i) Similar high error rates by leading research are already a fact.

(ii) The uncertainty of user trends and unexpected variations on the cost of IT services and devices.

In general, the overall approach of this thesis can be described to have certain levels of similarities with the MINTS and Bell Labs studies, yet with different parameterized techniques which has not been given much attention when compared to the rest of the literature. This is probably the first work on the static-adaptive field that relies exclusively on fixed attributes of pure numbers and on pattern detection of time series traffic data, rather than on dynamical properties of changing signals or other similar techniques. Furthermore, the following contributions may be also regarded as significant, since they are primarily addressed in the present thesis, and their prediction timeframe extends to 2018 inclusive:

(i) Characterization and projections of numbers of Internet users globally and how they relate to IP traffic volume growth.

(ii) Forecasting traffic at the Amsterdam Internet Exchange Point (IXP).

(iii) Introducing standard mathematical equations to predict the long-horizon aggregate traffic rather than for shorter time intervals that are limited to weeks or months. Effectively, the structure and parameters of the formulas can be updated with little effort and according to revised user trends, if and when it is indicated so.

At this point it must be mentioned that the unique way of approach by MINTS, Cisco Systems and S.K. Korotky as well as the negligence on the topic by research so far, is another motivation to conduct these studies.

1.5 Structure of the Thesis

The thesis contains ten chapters. The following part, chapter two, presents all relevant work in Internet traffic modelling and forecasting mainly since the 1990s, when the importance of the topic was raised, until the present days. The presentation starts with an historical overview of major traffic models and introduces the significance of making predictions in advance by analysing the Internet growth myths and facts and then proceeding to the details of the proposed forecasting techniques. Reported are the actual figures of the total Internet traffic worldwide, according to measurements published in different sources. Related studies on trends of global traffic are also highlighted along with their projections on future figures and growth. Emphasis is given to the literature that is more relevant with this thesis; the main achievements are described and certain problems are raised with some relevant observations and advices.

Proceeding to the core part of the work, chapter three focuses on the details of the methodology employed in these studies and what material has been used for the purposes of the new model and its advantages to make predictions. It is clearly shown why the suggested method is important, on what certain conditions it can be applied and how it can lead to accurate Internet traffic projections. The proposed methods are then put to use in the main chapters that immediately follow. In chapter four presented is a method and equation to make future predictions for the Amsterdam IXP and those are probably the first projections so far. For 2015, a very low prediction error has been achieved. Chapter five investigates hidden patterns in figures of available global IP traffic volume statistics and proposed is a new mathematical relation, relating IP traffic to the IP volumes of previous years. It is shown that the formula can indicate future traffic in very precise figures when comparing numerical results to existing projections from other studies, according to some measurements that are already available. Chapter six presents an alternative method to model and forecast global IP traffic, by assigning more dependence to the past in a different way, which is part from studies by the great mathematician Leonard Euler. As with the main formula to predict global traffic, this model has been also proved successful. Predictions of chapters five and six come with accurate figures for the proposed 3-year time frame, even though results of formula in chapter six is slightly above 5%. Similarly in chapters seven and eight, projected are figures on Internet users in the world and how they are related to the global IP traffic presented earlier. Therefore, two more new equations are produced, one of which with very precise results so far, and contributions are accordingly discussed. Next, in chapter nine, there is some further discussion on issues not entirely covered in the main part of the thesis and emphasis is given on some details. Finally, the epilogue chapter ten summarizes the proposed work. Important conclusions are highlighted and advice for ongoing work is given including research contributions from different disciplines. Appendices and the list of references are included at the end of the thesis.

CHAPTER 2

Literature Review

"Modelling is a form of abstraction and is a powerful tool in the lexicon of computer science"

- Vinton G. Cerf

This chapter is to describe the knowledge that exists in the area of characterization and prediction of Internet traffic. It provides a critical discussion of models and methods used and evaluates related achievements and contributions.

2.1 Fundamentals and Early Characteristics of Network Traffic Modelling

There are numerous extensive reports on the nature, applications, implications and growth of the Internet on a short, medium and long scale effect. Different proposed models and studies have initialized further in-depth research in Internet traffic since the decade of 1990. The self-similar characteristics of Ethernet traffic [Lel1994] and strong evidence of self-similarities on the World Wide Web (WWW) [Cro1997] were important achievements by that time. The narrower subjects of those novel studies triggered further investigation on closely related topics, including the establishment of appropriate models for certain scenarios but, simultaneously, updating some already existing facts. Regarding the latter, V. Paxson and S. Floyd (1995) have raised such an issue: even though network arrivals are well described with Poisson models, traces on Transmission Control Protocol (TCP) arrival sessions taken from 24 wide area network sources have revealed that these cannot be regarded as Poisson processes [Pax1995]. Furthermore, the primitive characteristics of network traffic, e.g. bursty nature, self-similarity, short (SRD) and long range dependence (LRD) motivated further research which was more QoS-driven (Quality of Service). Delay analysis, IP routing performance, queue lengths, inter-arrival times and distribution of packets at networking nodes are fine examples of complex QoS issues in traffic which can be well described using queueing systems. Theoretical queueing models proposed by Leonard Kleinrock for network analysis have been of major contribution [Cerf2012]. Principle concepts of queueing theory as analysed in [Kle1975], [Gro1998] and [LinFYS] outline basic characteristics of stochastic processes and calculations on memoryless models such as the simple M/M/1 and extending to more complex queue models. However, further studies in time raised numerous questions and proposed improved versions of the original models to address certain performance issues such as the analytic work by Kouvatsos (1986) reported in [Kou1986] and the distinct open queueing network models (QNMs) under three different traffic schemes as described in [Kou2003]. Moreover, when queueing systems are heavy utilized, studies by [Chen1993] suggested that functional central limit theorems can be employed to describe the associated service interruptions. Heavy tails are often observed in routes and paths generated from users sessions; a recent study described in [Arf2013] shows the Weibull distribution is able to model this feature at the inter-arrival level. More elegant characteristics of traffic behaviour have been further addressed such as the presence of LRD in time series [Taq1995], [Ber1994] and certain SRD issues by [Kou2000] and [Kru2000].

2.2 Measuring, Profiling and Analysing Internet Traffic

Traffic statistics can be categorized based on the timeframe in which they have been collected from. Depending on the scope, the time interval ranges from small samples during a day and may be extended up to weeks, months or years. For making predictions, the duration of measurements is critical while for some other purposes the volume of the sample can be flexible, such as the case for analysing the distribution of packet sizes in standard Ethernet connections. The distribution percentage of the sizes is roughly the same for numbers of packets in the order of millions. Such samples are observed at the Centre for Applied Internet Data Analysis (CAIDA), where statistics of monthly traces are captured within the USA at the Chicago and San Jose Internet data collection monitors that are with CAIDA and are each connected to a 10GigE (10 Gigabit Ethernet) Tier1 ISP link [Caida1], [Caida2], [Caida3], [Caida4]. Figure 3 illustrates the dispersion and the CDF (Cumulative Distribution Function) of the packet sizes captured at the Chicago traffic collection monitor on 15-10-2015, for approximately 1 hour and 2 minutes. The traces have been collected in direction A of the link (equinix-chicago.dirA). The total number of packets is roughly 1 billion (1003525648) of which ~95% are IPv4 and the majority of the sizes is seen at 40, 52, 1450 and 1500 bytes; all those packets together account for more than 60% of the total number [Caida2015a].

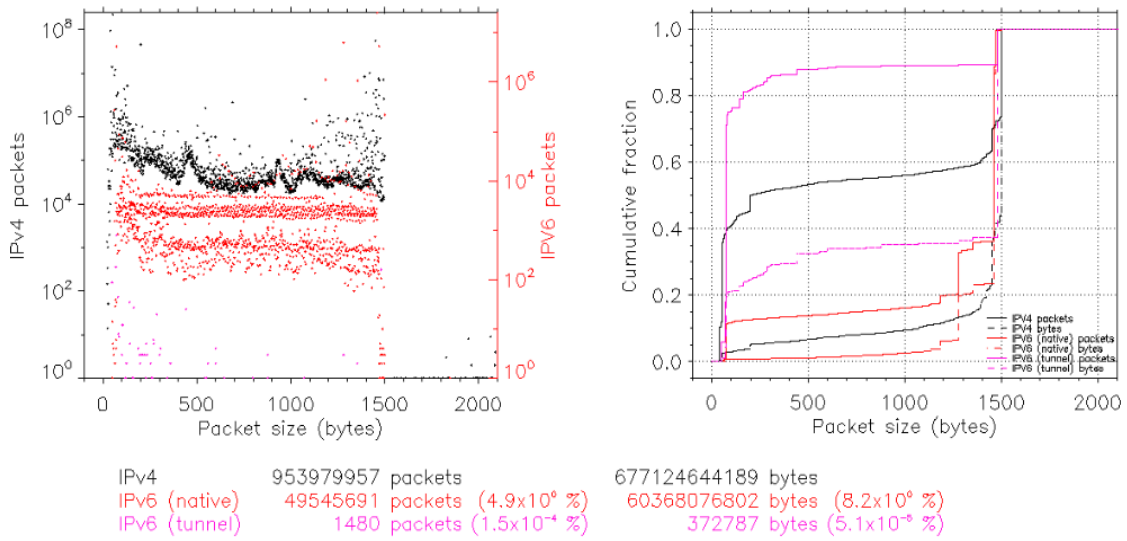


Figure 3: CAIDA statistics: IPv4/IPv6 and CDF fractions from approximately 1 hour of traffic [Caida2015b]

The way the distribution sizes are ordered is not at random and apart from that sample, most of the other collections on traffic traces listed in the tables at [Caida1] tend to be similar to each other and to figure 3. Furthermore, traffic captured at other locations as studied in [Gar2007] and [Gar2008] reveal high levels of IPv4 packet concentration at specific sizes that are generally in line with the traces collected from CAIDA (figure 4). Similar results of packet distribution at a different high speed link are reported from Reviriego et al [Rev2010], where almost 25% of all packets are near to 1500 bytes (figure 5). This value is the maximum transmission unit (MTU) for standard Ethernet frames [Gar2007], [Gar2008], [Rev2010], and on most Ethernet systems [Smi2010], [Vla2013b] and has not changed until today.

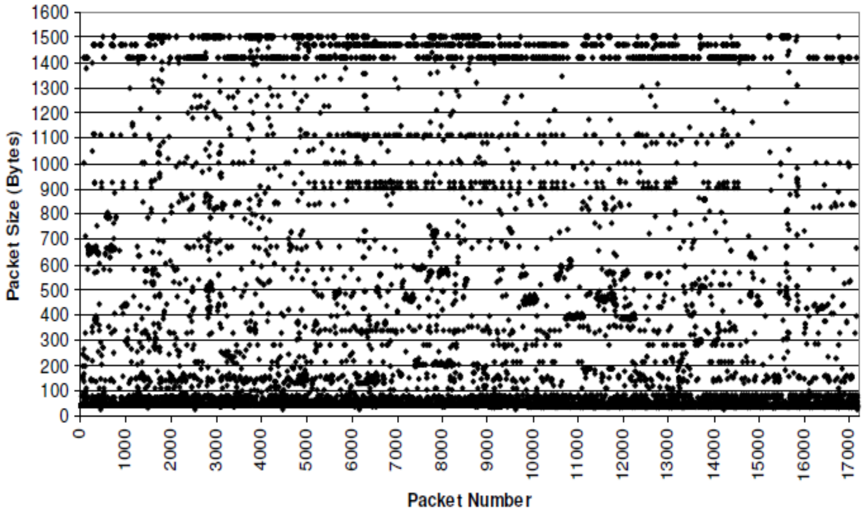


Figure 4: IPv4 packets [Gar2007], [Gar2008]

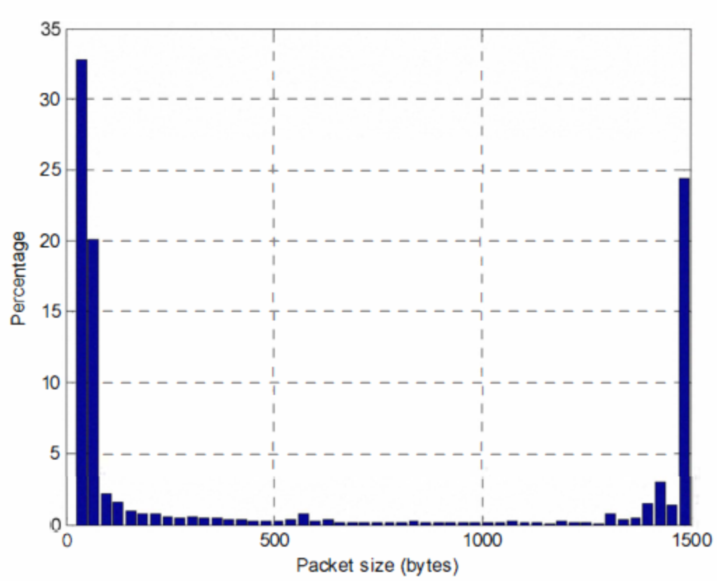


Figure 5: Ethernet packet sizes [Rev2010]

Of more importance are statistics collected from regional networks because they represent user characteristics and tendencies for longer periods. Studies on traces from a CDMA (Code Division Multiple Access) Chinese network have shown high traffic utilization rates from P2P (Peer-to-Peer) activities and overall results indicate that about 40% of the traffic volume and 50% of on-line time has been occupied by only 3-5% of the subscribers [Yan2011]. P2P applications and file-sharing software have evolved in the previous decade in both downloading and upstreaming. The traffic caused by P2P activities is a main source of traffic and has impact on the Internet [Bol2008]. P2P flow, as reported in [Lab2011], caused a 30-40% traffic share of the total Internet traffic in 2007, however its growth declined in 2007 to 2010. In contrast, nevertheless, a measurement scheme proposed by the authors in [Gio2013] has reported invisible P2P links from a total of 11 Internet exchange points (IXPs) and the number of these invisible links reaches 36000.

The dominating nature of P2P file sharing is also addressed by J. Li et al [Li2012], whose studies come from long period measurements (June 2007 to May 2011) on a Swedish municipal network. One of the most important results is, for those 5 years, the daily average total traffic from end users has grown ~33% [Li2012, p.1]. The significance of this observation points to the long term evolution of Internet user trends, since the data sample comes from a long time effort. The primitive characteristic of the traffic captured for several consecutive years is that it can indicate future trends, which is the main topic in this thesis. Furthermore, of note is the analysis of traffic from an academic network in Lithuania of which traces have been captured with the NetFlow for two different intervals, one month and one semester (4 months), sorted by protocols [Gars2012]. The results (figure 6) show similar tendencies on the two timeframes even though they are different.

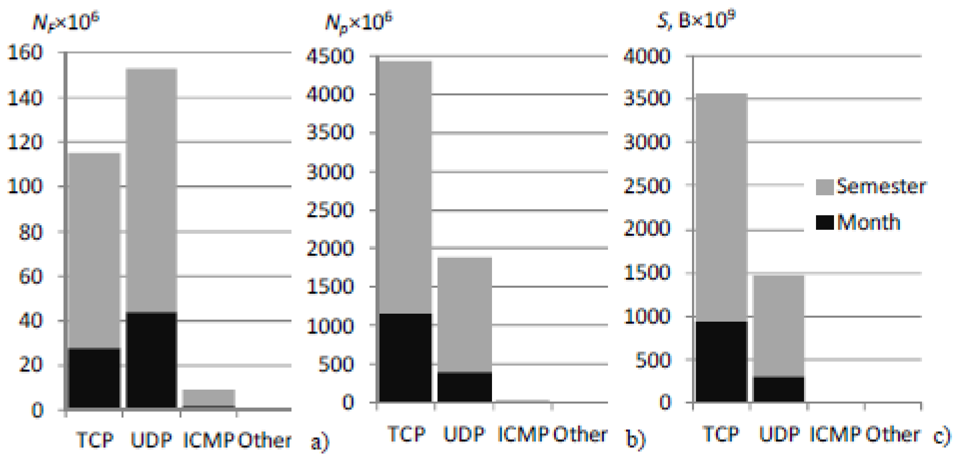


Figure 6: Protocol distributions for (a) number of NetFlow (b) packets (c) volume of data [Gars2012]

It is obvious that the semester to month volume ratio for both TCP and UDP protocols in figure 6.C remain approximately the same and, considering the 4x relation of the associated periods (4 and 1 month), we can observe a close to 4x relation for the TCP to UDP ratio too.

The macro trends and implications of long term traffic collections and the penetration of portables, smart TVs and mobile entertainment applications tend to receive more attention. Although certain user tendencies are known on medium scale timeframes, e.g. online behavior through a week, mainly in the last several years it has come to our attention to characterize activities over long periods. The sinusoidal shape for a typical day-to-day Internet traffic with maximum and minimum activity seen at daytimes and at night respectively is well known [San2014] but appears to be different than much of the long term year-to-year aggregates. Regional measurements across different countries and ISPs demonstrate the growing nature of the Internet, such as the 4-years trend of bandwidth usage in North America [San2014] and a 6-months traffic accumulation from 5 observed ISPs [Ans2015]. The latter reports an average monthly growth of 41% (figure 7) but the respective peak growth rate is calculated at 80% [Ans2015, p24]. Although we can observe some decline within small periods, all the generated traffic is generally increasing.

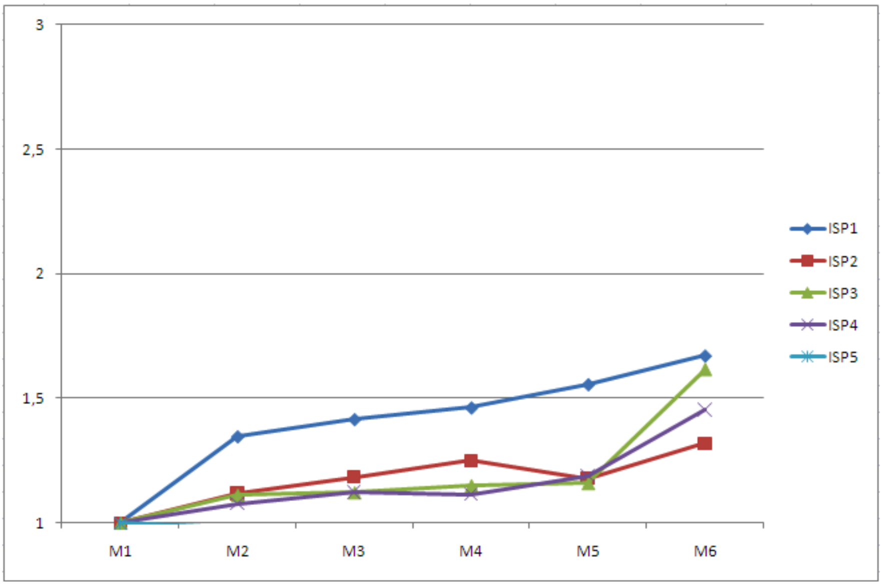


Figure 7: Traffic growth at five different ISPs [Ans2015]

On a similar basis but rather a longer trend illustration is the next graph which exhibits higher levels of growth. Web aggregated traffic is shown (figure 8) as a percentage of the total traffic in the United Kingdom from September 2009 until July 2011. More than 50% of the traffic in the UK originated from i-phones, while the rest came from other devices like i-pads and blackberries [Tecm1]. The same company predicted that by January 2012 the mobile traffic will be more than 15% of the total UK, if the growth rate continues like that of previous six months [Tecm1, p.9]. Likewise, in the entire world, the traffic coming from smartphone users is on average ten times more than the traffic generated by other type of users [Sol2011]. In general, mobile traffic is becoming a significant part of the global flow as users increase in time. There are considerable efforts in networking updates and expansions, yet it is difficult to satisfy the large number of users with high traffic portions [Cui2014].

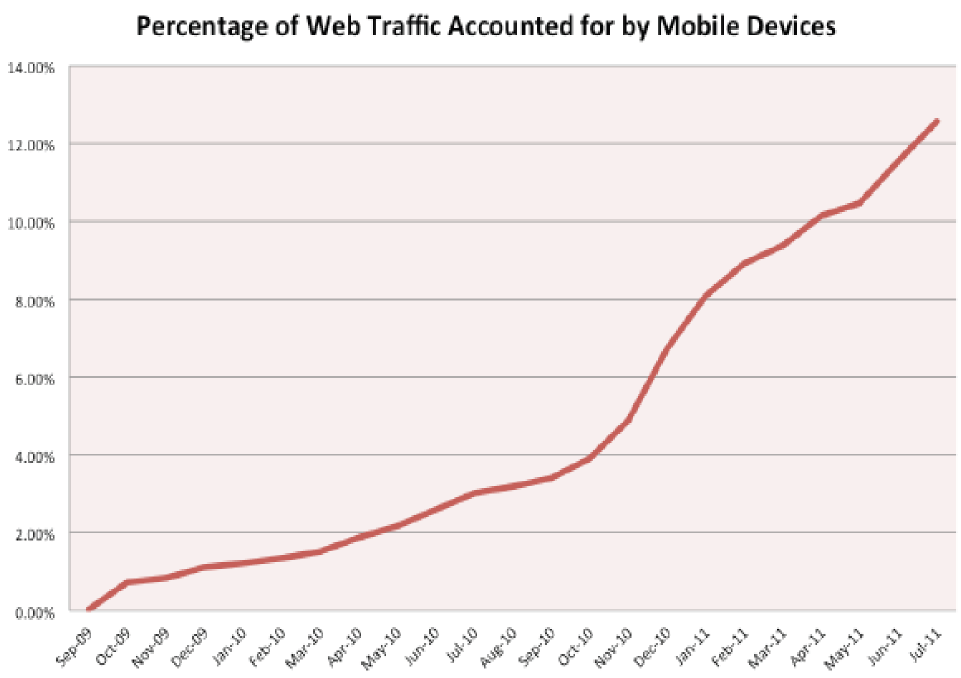


Figure 8: Mobile Web traffic in the UK [Tecm1]

We can observe a slight change of the trend around October-November 2010 due to the technology advances in mobile devices and the dominating video sharing and real time entertainment streaming websites. Two of the finest examples, and responsible for large portions of generated traffic, are Netflix and YouTube [Hor2015]. In 2007, a three-month observation on YouTube traffic reported almost 25 million transactions including over 600000 video downloads [Gil2007]. This massive video-generating service is the leading traffic source all over the globe and accounts for a large share of the total mobile traffic as well [Hor2015]. Furthermore, in 2014 the Internet Protocol (IP) video traffic has been estimated at 67% of the entire IP activity on a global level [CisVNIb]. For wireless networks, nevertheless, there is often a need for stronger traffic management than for fixed infrastructures [Jor2011]. Mobile traffic is definitely growing at higher rates compared to the wired or total IP traffic as seen in table 1 available from Cisco. Due to the interaction between unicast and multicast flow as well as with different types of IP versions, the necessary requirements must be addressed in Internet traffic engineering and the peculiarities of multiple traffic sources must be considered [WanN2008]. In order to address those issues, accurate traffic traces from all sources are essential. However, the dynamic characteristics of the Internet and the inconsistencies of the heterogeneous structure of traffic sessions raise a fundamental question: how precise are the measurements taken either for short or long time intervals and is there any information loss on the data captured?

2.3 Are Measurements Accurate?

Traffic modelling is a vital part of networking design and thorough analysis of historical traces and their models can maximise performance [Kar2004]. Certain measurements of Internet historical activity have been reported and are available from the University of Minnesota in [UoM1]. In addition, the aggregation of the flow of various traffic sources is likely to indicate accurate statistics of the totality of Internet traffic. Consecutive and successfully captured traces can give accurate estimates of Internet traffic volume growth which, in turn, can predict the short and/or long term global volumes [CisVNI], [UoM5]. Estimating Internet aggregate volumes growth ideally means we have absolute precise historical figures from pertinent measurements. Accuracy must be a prerequisite when performing estimations due to the significance of the issues involved such as IP networking updates, hardware resources planning, energy consumption and spending cuts. Computer science and economics are the major fields to benefit if the traffic-capturing processes are performed on an accurate basis. But do measurements always come with precise figures?

The process of forecasting worldwide traffic by investigating traffic from past years, means we have sufficient data of the historical Internet activity. Although the Internet is a large and complicated networking system connecting many smaller networks, there do exist some historical data including important information as reported in [Kor2013], [Cis2013], [Wik2015a], [Vla2015]. All heterogeneous information that crosses the entire Internet along with the distributed infrastructure of most networks are undesired circumstances for accurate traffic capturing. Inevitably, certain loss of information may occur and this can lead to imperfect data collection. By looking carefully at all historical figures included in relevant tables from [Kor2013], [Cis2013] and [Wik2015a], we can observe different numbers on the aggregate traces of the worldwide fixed Internet volumes. But even though figures are not exactly the same, there are significant similarities which they are common in all tables. In particular:

(i) There is a stable increase in the fixed Internet and the global IP volumes, as these are progressing in time.

(ii) In terms of annual growth, i.e. year over year, the rate exhibits constant decaying characteristics especially in the last years.

Observations derived from (i) and (ii) confirm the expected increase of the total global traffic on a yearly basis; however the respective growth rate tends to decline. The numbers presented in table 3 illustrate the totality of information of IP, fixed and mobile aggregated flow while table 4 shows the fixed Internet traffic part. Table 3 is an explicit sample of an extensive trace set taken from [Cis2013] and [Wik2015a] and table 4 is part of studies by Steven K. Korotky in [Kor2013]. According to those three sources, however, all the original information has been extracted from networking company Cisco.

Global Internet Traffic by Year	**Traffic in Petabytes (PB) per Month**		
	IP Traffic	***Fixed Internet Traffic***	***Mobile Internet Traffic***
2005	2,426	2,055	0.9
2006	3,992	3,339	4
2007	6,430	5,219	15
2008	9,927	7,639	38
2009	14,414	10,676	92
2010	20,197	14,929	256
2011	27,483	20,634	597
2012	-	31,338	885

Table 3: Global collected traces of IP, wired and mobile traffic [Cis2013], [Wik2015a]

Year	**Fixed Internet Traffic (PB/Month)**	**Traffic Uncertainty (%, Relative)**
2006	3,683	20
2007	5,419	15
2008	8,140	10
2009	10,943	7.5
2010	14,955	5
2011	23,288	5

Table 4: Global fixed traffic [Kor2013]

In spite of the variation of the fixed global part, the data certainly outline the increasing nature of the associated volumes and some decline on the AGRs is observed more or less in a stable pace. Company Cisco Systems is a leading research body in estimating traffic aspects which rely on different sources, e.g. on Internet connections, analysts, Internet Service Providers and various companies [Cis2014b]. Studies through their project named “Visual Networking Index” (VNI) provide regional and global forecasts on Internet traffic and numerous other related categories [CisVNI], [Cis2014b]. As far as relevant terms are concerned, “fixed Internet traffic” probably refers to all ISPs including residential and business services, cable connections etc., while “mobile

Internet traffic" is perhaps the generated flow coming from mobile phones and their ISPs [Wik2015a]. "IP traffic" probably includes all the networks and those that are closed, but use the IP such as IP television (IPTV) [Wik2015a]. As pictured in table 3, most of the worldwide IP traffic originates from wired technologies and this can be observed through all years until 2011. However, by taking a close look at the fixed Internet traces in tables 3 and 4 we can observe some considerable differences on the information in period 2009-2011 inclusive. In any case if there are different observed volumes for the same type of traffic, these must not be neglected in any way. As such, some important issues must be seriously taken into consideration:

(i) The quality of the investigation on different historical information that should be almost identical.

(ii) To what extent are inaccurate historical samples to adversely affect the precision of traffic we expect for the future.

In tables 3 and 4 and for the fixed part of traffic, there are some significant deviations in the numbers that represent the volumes of the same years. If one produces an equation to make predictions based on the wrong patterns for the given data set, then there might be concerns regarding the efficiency of the formula. The variability of the data does not encourage research in order to produce one and only mathematical relation that would be based on the static nature of those measurements. In general, the measurement quality is a main factor and there are numerous studies of which subjects rely on accurate traces. In [Kih2010] it is stated that using Packet Logic, more than 95% of the traces can be identified to analyse traffic measurement from a broadband network, while Kundu et al raise traffic accuracy issues as well [Kun2009]. The latter propose a new traffic measurement scheme to collect specific traffic flows that are difficult to capture and this can be done with more or less 90% accuracy [Kun2009, p.112]. Consequently when considering those reports, a 100% absolutely precise sample of traffic may be difficult to achieve and at least some occasional loss of information does occur, even if state-of-the-art techniques are employed to capture the distributed traffic of the Internet of networked systems.

2.4 Modelling and Predicting Internet Traffic using the ARMA Models

There are different studies presented by different forecast models with a variety of techniques and for different time scales. In [Cor2006], the authors mention there are four prediction horizons that are commonly accepted, starting from the shortest: real-time, short-term, middle-term and long-term [Cor2006, p.2636]. The latter is the case of study in the present thesis. However, all definitions apply to related work in time series forecasting of which one of the most popular is the Auto Regressive Moving Average (ARMA) model and its variations, e.g. the Auto Regressive Integrated Moving Average (ARIMA). This stochastic model is used in statistical analysis of observed time series data and has very good prediction results in related studies such as the ARIMA proposed in [Szy2012] for bandwidth allocation. Real traffic every 15 minutes over a long period of 4 months has been collected from a major backbone in Europe and the proposed estimation algorithm operates at a success rate between 93% and 99% [Szy2012]. Pictured in figure 9 are results on forecasting traffic over 7 days compared with the actual data and we can see the almost perfect match.

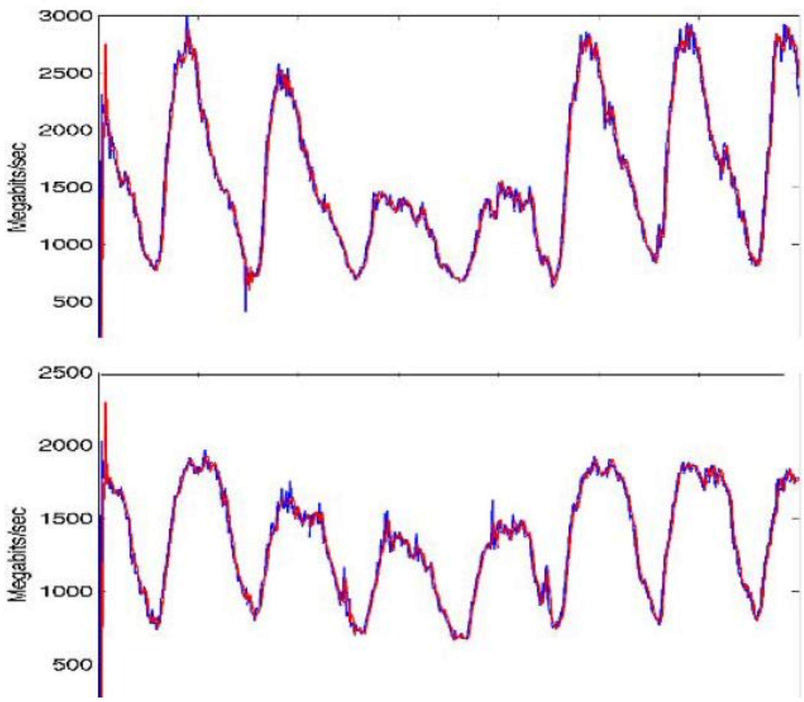


Figure 9: Actual (blue) and estimated (red) traffic in seven days period [Szy2012]

The same model is used for network traffic prediction named "Traffic Oblivious Routing and Scheduling" algorithm as studies by Prashanth et al (2009), where traffic is projected according to the information on the past activity [Pra2009]. Moreover, the ARIMA process is the reference model in a different study. Here, the subject is predicting certain trends and socio-economic aspects of Internet users in China, categorized by gender, age and income [Sin2011]. Internet traffic is generated mainly by users and it is very important to know how they behave in the market. It is suggested that modelling Internet traffic volumes requires a good understanding of the traffic coming from individual users [Det2003]. According to the authors in [Sin2011], the number of users is estimated to reach ~1.53 billion by 2015 and the following detailed information is reported in table 5, including corresponding errors in terms of Mean Absolute Percentage Error (MAPE). It is mentioned in [Sin2011] that, according to some other studies, if the MAPE is lower than 10% then the prediction result is accurate and between 10% and 20% forecast results are good. We can see this acceptable range of errors in five results on forecasts in table 5.

ARIMA model	Indication	Forecast Error			
		RMSE	*MAE*	*MAPE*	*Theil Inequality Coefficient*
Interenet user (1,0,0)	Increase	16923541	11848619	11.9	0.04
Female (2,0,2)	Stagnant	0.03	0.02	6.2	0.03
Male (1,0,0)	Decline gradually	0.02	0.02	4.1	0.02
Age < 21 years old (1,1,1)	Increase	0.07	0.06	32.8	0.15
Age 21-30 years Old (1,0,2)	Stagnant	0.05	0.03	5.9	0.1
Age > 30 years old (1,1,1)	Decline gradually	0.05	0.04	23.2	0.1
Income < 501 yuan (1,0,0)	Stagnant	0.05	0.03	26.6	0.1
Income 501- 4000 yuan (1,0,0)	Stagnant	0.06	0.04	7.3	0.04
Income > 4000 yuan (2,1,2)	Increase	0.01	0.01	22.4	0.15

Table 5: Demographic projection results of Internet users in China [Sin2011, p.80]

Predicting network traffic with ARIMA can be employed for smaller scale areas as well, such as for a mobile Wi-Max range and have also good performance in forecasting results [Kim2011]. However, an improvement over the primary ARIMA model is the topic of El Hag and Sharif (2007), who propose an Adjusted ARIMA (AARIMA). The model is able to capture the self-similar characteristics of network traffic while at the same time it does not exclude any of the elegant properties of the original ARIMA methodology [ElHa2007]. Results of the new proposal show considerable improvements in Mean Absolute Error (MAE) and self-similarity. However, regarding the latter, it is has been reported that the self-similar nature and its characteristics are often a disadvantage for traffic forecasting and can cause certain difficulties [Gar2007], [Min2005]. In a similar way, network congestion is another undesirable phenomenon which has a negative impact on certain issues such as packet loss increase and limitations on network services forecasts [Awd2002]. However, some high-quality studies like the following highlight important aspects of Internet traffic.

A comprehensive work on a multiple timeframe scale on traffic predictions with a wide range of useful results comes from Papagiannaki et al (2005). The study uses collected traffic from simple network management protocol (SNMP) measurements from 1999 until the end 2003 to perform estimations mainly for the long term [Pap2005]. The reference model is the ARIMA and the approach that has been employed calculates the average aggregate demand between any two points of presence (PoPs). Initial observations from three sets of traces, each between two neighbouring PoPs, show a steady-like increase of the average bandwidth demand in two out of three traces in the long term (figure 10).

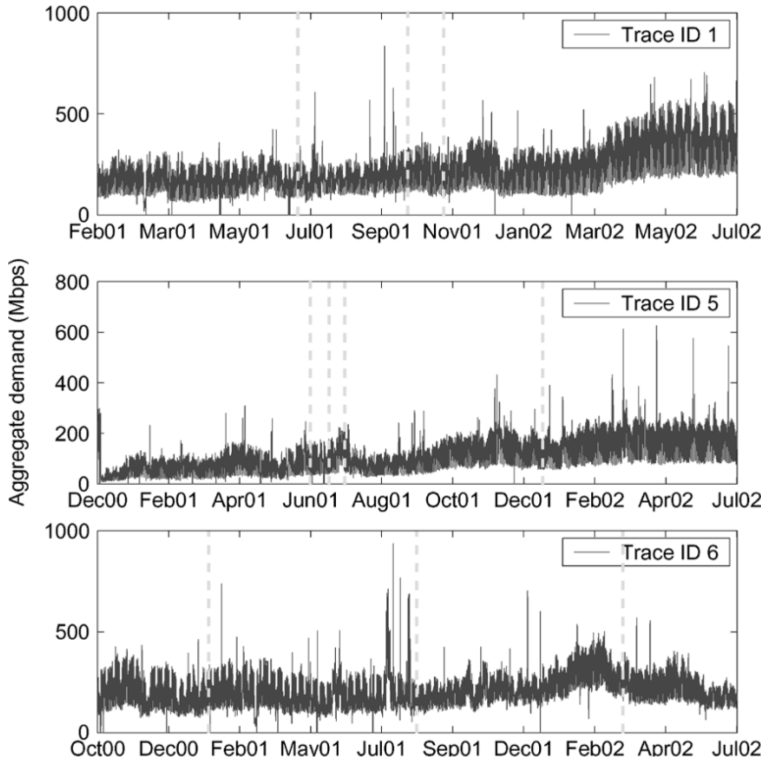


Figure 10: Traffic trends of the average demand [Pap2005, p.1112]

The sample of traces 1 and 5 in figure 10 suggest there is a certain rate of growth over the long term and if the trend continues more or less at this rate, then predictions on this basis can be accurate. In the next figure, however, pictured are the same traces but on a monthly scale (figure 11), that of May 2002 (1^{st} – 31^{st}) in which there is strong evidence of diurnal patterns and persistent cycles [Pap2005, p.1113]. Those graphs, if extended horizontally, may have certain similarities with the day-to-day sinusoidal shape from several consecutive days' traffic presented in [San2014] and the 24-hour activity shown in a UMTS report [Umts2011, p.63]. Moreover, it seems there are no signs of overall growth during the 31-days period and this may be due to the considerably smaller sample as opposed to the more representative and mass traces of figure 10.

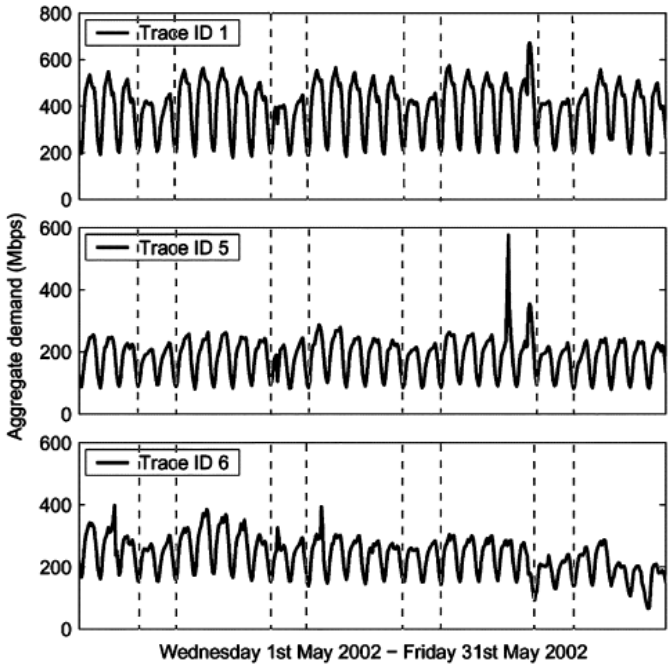


Figure 11: Traffic trends during May 2002 [Pap2005, p.1113]

At the final stage, prediction attempts are performed according to the historical trend of trace ID 5 of figure 10. The forecast horizon is set to six months and to one year and then estimates are evaluated with reference to the actual traffic. Figure 12 shows predictions over the next six months and figure 13 extends forecasts up to a year, each of them presented on the right hand part divided by the dotted vertical line. The error rates are reported on a short and long term basis. Over weeks the average forecast error is – 3.6%; for all five traces that have been used in the studies the absolute relative prediction error is calculated at less than 15% on average for the six-month horizon and 17% on average for a whole year [Pap2005, p.1119-1120].

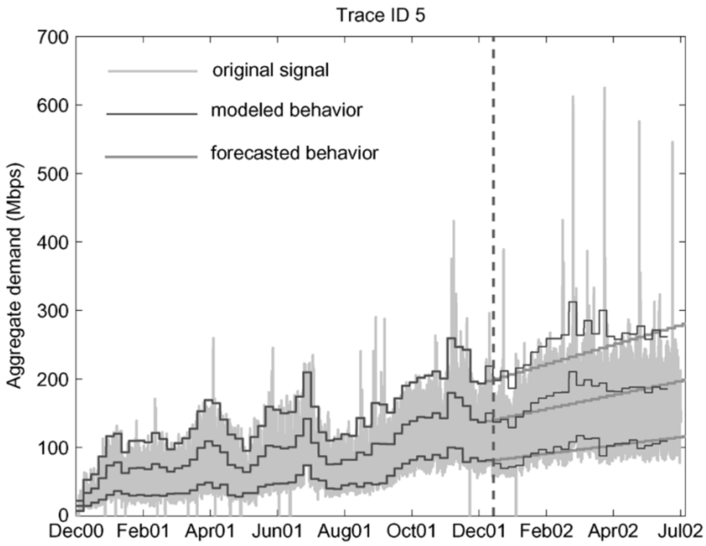


Figure 12: 6-month traffic predictions and evaluation for trace ID 5 [Pap2005, p.1119]

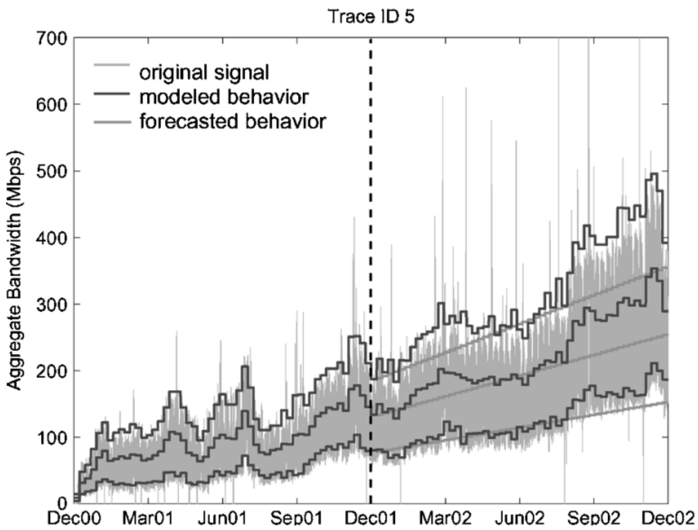


Figure 13: 1-year traffic predictions and evaluation for trace ID 5 [Pap2005, p.1119]

Finally, extreme prediction cases are as well addressed in the same studies. In the next graph, additional forecasts on a 6 and 12 months' timeframe are presented and added is a 95% confidence interval and a fitting line that characterizes the overall trend and has the following expression [Pap2005, p.1121]:

$$y = \alpha \cdot \chi + b \tag{2}$$

We can observe the fluctuation spikes of the actual data and some extreme forecasts for June 2004:

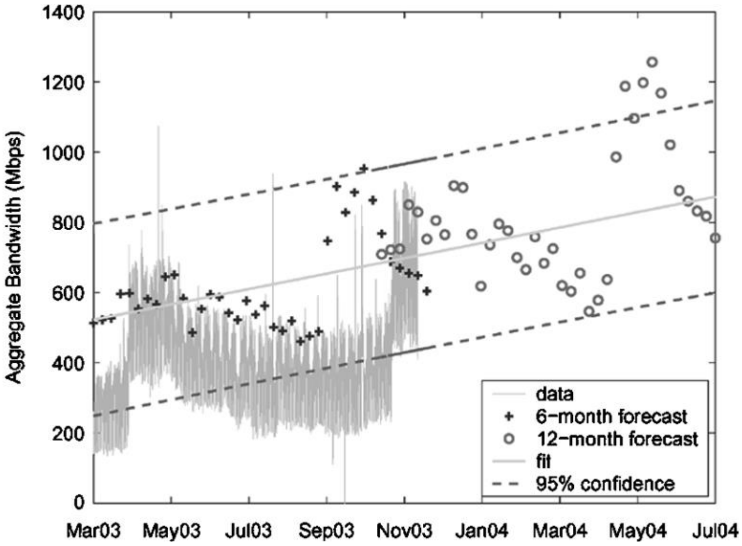


Figure 14: Linear trend line, confidence space and extreme values [Pap2005, p.1121]

In further different studies, fractional ARIMA (FARIMA) methods give better forecasting performance than models based on Auto-Regressive methods such as in [Shu2001]. A combination of three models – the AR, the MA and the FARIMA – is presented in another reference, demonstrating the compound hybrid model has enhanced prediction accuracy [Wen2008]. A similar study uses combinations of the ARMA and FARIMA models to forecast traffic in a 3G mobile Chinese network [YuY2013]. The authors point out that the FARIMA fails to model the multifractal characteristics of Internet traffic and therefore the proposed combined model has very good results. Reported are considerably low errors: the MAPE has been computed at ~2.25% and the highest APE is at 7.73%, both of them within the most acceptable [0%-10%) error rate interval which is defined in many studies as "accurate".

Last but not least, a generalization of the genuine ARMA and ARIMA models is the Seasonal ARIMA (SARIMA). Studies by Syed et al (2010) propose a wavelet-based SARIMA suggesting better forecasting performance than ARIMA [Sye2010] while another study performs predictions based on traces from a backbone network. Specifically, the authors in [Oto2015] use three different methods (illustrated in (a) to (c), figure 15) to predict traffic on a several-hours basis, by employing both ARIMA and SARIMA. The method uses the trained data from the collected traces to produce predictions. One packet out of every hundred packets is captured and the accumulated traffic is formed every five minutes, while the totality of measurements extends to four weeks. Numerical results show exceptionally low MAPE rates but it seems that the sudden spikes caused by users cannot be captured, thus resulting in higher forecast errors [Oto2015, p.43-44]. On the other hand, such peaks are not observed in larger flow samples but even if spikey flows are present, their impact is insignificant to large flows when the flow extends to a large number of users [Oto2015, p.44]. Concluding this important study, the authors claim SARIMA is suitable for long horizon predictions while the ARIMA can accurately capture near term traffic. Examples of their forecasts are as pictured in the following figure.

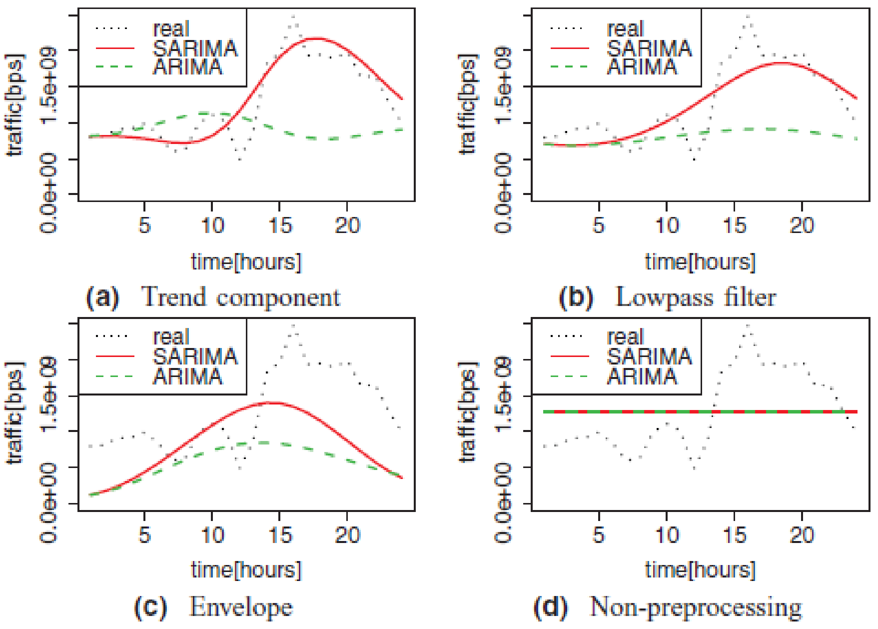


Figure 15: Predictions using ARIMA and SARIMA vs. real traffic [Oto2015, p.43]

2.5 Neural Network Models

Precise traffic estimations is a hard challenge and Internet traffic is one of the most unpredictable aspects [Kam2014]. Through numerous high level studies, however, it is accepted that estimations on Internet traffic suggest considerable growth in the next years [Ard2012] [Cis2015] and the traffic generated by communication networks continues to grow on a global scale [Cis2015] [Kor2015]. Depending on the timeframe, Neural Networks (NNs), or Artificial NNs (ANNs), are widely used models for traffic estimations. They are based on a large number of unknown inputs such as the incoming signals of traffic traces which can be well described using appropriate types of Neural Networks. Unlike the ARIMA model, which fits linear equations to stationary training data, ANNs are non-linear methods [Bab2015]. Predictions with NNs have very good results and high accuracy, such as the studies from Loumiotis et al in 4G networks [Lou2015]. They propose a new scheme able to predict the traffic aggregated at base stations (BSs) in mobile 4G technologies by employing ANNs, with a mean absolute percentage error (MAPE) calculated at around 10% for downlink traffic and ~19% for uplink traffic [Lou2015]. In terms of another type of error – the normalized mean square error – studies on forecasts on Ethernet traffic using “a Multiscale Bilinear Recurrent Neural Network with Adaptive Learning (M-BRNN-AL)” report higher prediction success than some other BRNN models [Par2010]. A different type of traffic, namely video traffic, is the subject investigated by Y. Liang (2004), where multiresolution learning can boost NN predictability performance and the suggested predictor has successful results in forecasting real time variable-bit-rate (VBR) video flows [Lia2004]. For Ethernet traffic, another NN-based study comes from Auld et al (2007) who introduce training data on a Bayesian neural network and provide traffic classification using efficient techniques in which packet access is not required [Aul2007].

Predictions using Neural Network techniques accommodate small errors and they are usually targeted for real time and short term estimates. An efficient high-accuracy forecasting model by a genetic algorithm is proposed by Lu, W. (2014) in which numerical experiments indicate an average relative error (ARE) as low as 2.322×10^{-2} [LuW2014]. This value is achieved with a joint optimization model of two parameters and is nearly three times lower than the value calculated using the independent scheme [LuW2014, p.699]. Another genetic algorithm is proposed by Wang, C. et al (2008); however, here the error rate is higher but still remains at low levels and calculated at 8.18% which is the best selected value [Wan2008]. In addition, a more accurate sample of error calculations on an improved BP Neural Network is performed to compare a set of predicted results with the actual traffic. For a set of traffic observations over ten consecutive days the error range has been calculated at 0.39% minimum to 3.81% maximum [LiZ2009]. However, the authors point out that for ongoing research bigger samples of traffic data are required [LiZ2009, p.38] and this may imply better prediction accuracy could be achieved if studies are based on larger quantities of captured data. Furthermore, a wavelet NN is proposed by Zhao et al (2005) where the traffic dataset has been collected over two months. The suggested model is compared with a non-wavelet NN and reported are a maximum relative error of 6.464% and a maximum average relative error at 11.2345% [Zha2005]. On the same path, a novel wavelet NN is presented in [Zhang2012], the Recurrent Wavelet Neural Network (RWNN), and a time series traffic is recorded over one week in September 2010. The performance of the proposed version is put into test with other NN models and results show RWNN has better error rates in terms of mean square error (MSE). Finally, very important results are also obtained in an aggregation of traffic data from JANET and a private ISP across eleven cities in Europe [Cor2006]. The paper presents a NN Ensemble (NNE) which is highly competitive to other models including the popular ARIMA. The associated forecasting performance is calculated using the Mean Absolute Percentage Error (MAPE) and almost all results have lower error rates, ranging from 1.43% (±0.01) to 28.37% (±0.8) [Cor2006, p.2640]. Further observations of the results report very good prediction accuracy in real time traffic but higher deviations when expanding the forecast timeframe. Specifically, estimates for five minutes ahead have an error at 1%-3% and this percentage climbs to 11%-17%. When the procedure switches to the short term, the error starts at 3%-5% for the 1 hour interval, increasing up to 12%-23% for 24-hours target [Cor2006, p.2641-2642].

Regarding the overall performance of NNs/ANNs compared to the statistical models, it has been reported that traffic forecasting accuracy of NNs is as high as between 96.4% and 98.3% and the corresponding rate of statistical models, such as the FARIMA, is found at 78.5% to 80.2% [Gow2008]. Another more recent study suggests that the hybrid combination of FARIMA and NN models is the most efficient approach to predict Internet traffic [Kat2015]. The authors claim that this advantage is a result of the presence of non-linearity in those hybrid models.

2.6 Further Studies on Modelling and Predictions

Apart from statistical time series models, there is a wide range of studies using different techniques including hybrid processes and Markov models. The latter is a subject of Internet traffic analysis by Muscariello et al (2005) and a Markov Modulated Poisson Process (MMPP) is proposed to capture the LRD characteristics of network traffic and the model can be used for IP planning and design purposes [Mus2005]. Furthermore, a Markov model is proposed for predicting Web users' behaviour [Don2002] while in [Dai2008] a hidden Markov model (HMM) is able to estimate certain parameters at the packet level and indicate short term traffic. A more heterogeneous approach is presented in [Yao2006] and [Xie2015]. In the former, the proposed method is based on an integration of wavelet and NN, and is compared with a BP NN and an Auto-Regressive(6) model. Results show it is more competitive than the other two models with reference to the Root Mean Square Error (RMSE). The later describes the traffic at a node a with Markov chain model and estimates traffic in a heterogeneous Carrier Sensing Multiple Access with Collision Avoidance (CSMA/CA) network using an ARMA particle filter, which outperforms current methods [Xie2015].

From a different approach, seasonal GARCH models are reported for Internet traffic prediction [KimS2011], a combination of fuzzy systems and NNs for traffic estimations [Cha2009] and a Kalman filter to predict traffic volume on the short term [Gong2013]. Finally, worth mentioning are the following two studies. In [Dai2014] an EMD-based (Empirical Mode Decomposition) multi-model Prediction (EMD-MMP) algorithm is proposed using history traffic and appears more efficient than the ARMA and the Support Vector Regression (SVR) models. Studies by Ganguly et al (2015) introduce a Lagrange polynomial and a regression formula to predict the position of Delay Tolerant Network (DTN) nodes; the regression equation is of the following expression and more details of parameters a, b and c are outlined in [Gang2015].

$$y = a \cdot x^2 + b \cdot x + c \qquad (3)$$

2.7 Macroscopic and Very Long Term Projections

This section is to demonstrate various attempts on Internet traffic forecasting, mainly in terms of total volumes or aggregate bandwidth demand, looking ahead for at least a few years. The self-similar characteristics and non-linear nature of Internet traffic may cause inaccurate forecasts [Wu2009]; however this usually occurs when making predictions on short time scales. Long term trends behave independently from the dynamic characteristics of the self-similarity and there is some evidence that year-over-year traffic variability tends to be smoother when compared to the changes that traffic exhibits for short time periods. This feature is more evident when forecasts are performed for large geographical areas. Some reports and journalists have claimed the growth of Internet traffic around certain regions is described as exponential, but it was believed this was a myth as demonstrated by Odlyzko (analysed in section 2.8). Numerous studies or other sources of measurements suggest that annual growth has been slowing down over the last several years in many large geographical areas and globally. Moreover, the decrease of annual growth rates is estimated to continue in the future and remains a subject of research. The next figure shows projections on fixed Internet and managed IP traffic worldwide in aggregated volumes, with their respective growth rates (reddish brown line).

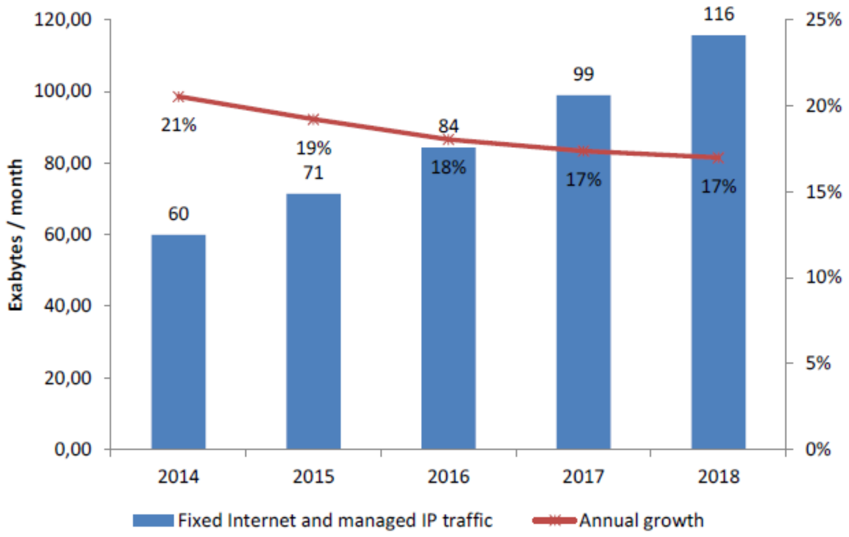


Figure 16: Estimates on global Internet traffic volume [Mar2014]

In general, IP traffic total volumes do increase on a global scale over time, with corresponding declining AGRs, and the traffic growth "is partly a function of an increase in the number of subscribers, and partly a function of an increase in traffic per subscriber" [Mar2014, p.26]. This may imply a hidden formula or a regression equation between two or more parameters for each of those functions. More or less, similar speculations on the growth towards year 2020 are displayed in figure 17, in terms of compound annual growth rate (CAGR).

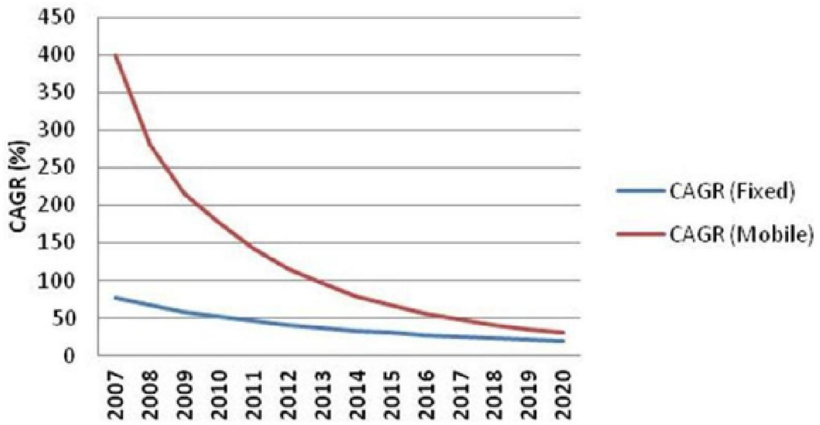


Figure 17: CAGR for global fixed and mobile traffic [But2013, p.11]

An important observation on both CAGRs of figure 17 when combined with the historical data of table 1 (chapter 1, section 2) is the even higher growth rates of the mobile traffic part compared to the fixed, even if the latter accounts for larger volumes. The usage of mobile devices and certain applications on smart phones, i-phones and portables are consuming more traffic than in the past. A relevant study has estimated that a 66% of the overall mobile activities will come from communications and video streaming by year 2016 [Sand2014]. IP video itself is responsible for a big portion of traffic in metro networks [Bell2013] and the growing tendency of video services seems to be a fact for the whole Internet mainly because of the popularity of traffic-consuming giants like YouTube and Netflix. However, the uncertainty of user trends may produce inaccurate predictions and, instead of giving projection with fixed numbers, ranges might be a safer option. In the next graph (figure 18) extrapolated are projections until 2020 using a minimum and maximum limit and the estimated growth range indicated on the right may be the average of the highest and lowest forecasts. The graph comes from the ITU-R M.2290 report [Sand2014]. The assumptions of making (very) long term forecasts depend on the methodology and the approach. Different studies can give completely different results especially towards the far future as pictured in figure 19. We can observe results close to each other in short terms, even though the gap increases as we approach the final year. Cisco, Alcatel-Lucent and Morgan Stanley (2012 and 2013) seem to be on the same line but projections for 2015 from the former two are quite different from others.

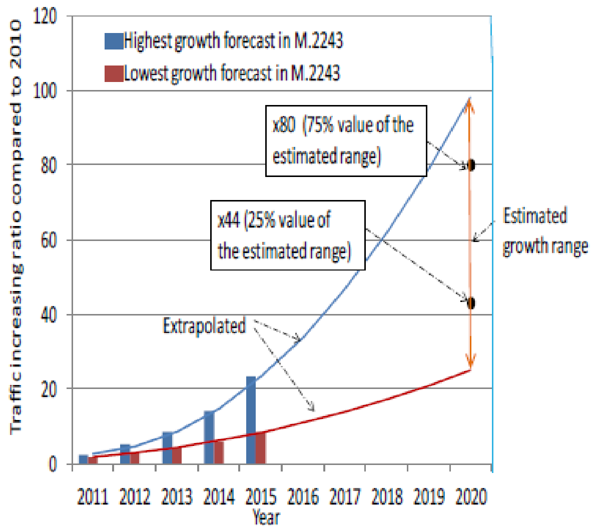


Figure 18: Extrapolated estimates [Sand2014, p.13]

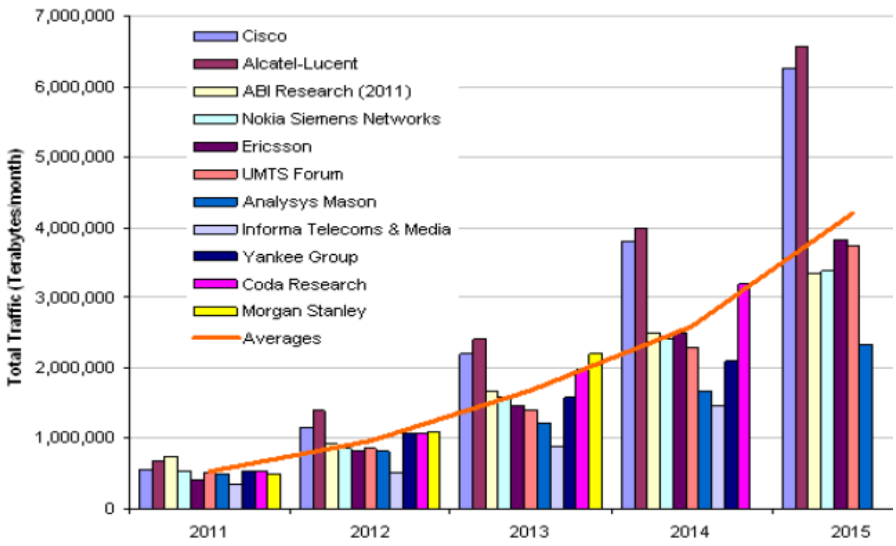


Figure 19: Forecasts from various companies [Sand2014, p.9]

The complexity of the scaling behaviour that Internet traffic exhibits is very challenging for prediction studies [Mao2005]. Different market technologies and innovations add more to the challenge considering the technological advances in the last few decades. One of those advances is the bandwidth offer but research efforts rather focus on the bandwidth demand. Nielsen's law of Internet bandwidth states a 50% growth from year to year in high-end user's connection speed [Nie1998], [Hars2015] and is "10% less than Moore's Law for computer speed" [Nie1998]. Of more important note is the fact that the law fits respective bandwidth data from 1983 to 2014 on a X-Y coordinate system of which the Y-axis is on a logarithmic scale and thus represents a straight line [Nie1998] shown in the following figure.

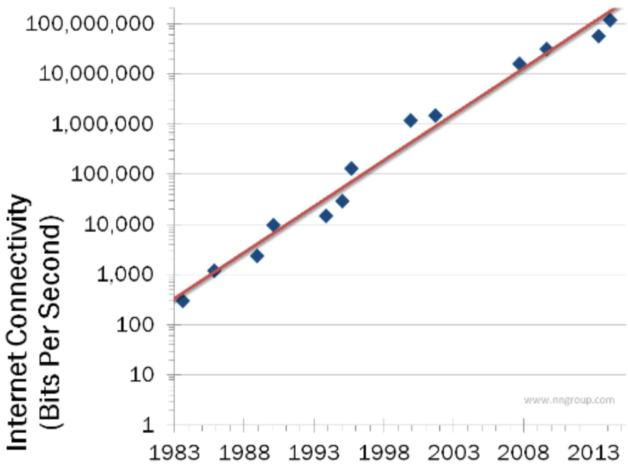


Figure 20: Nielsen’s law: fitted data [Nie1998]

However, the law states only the bandwidth that is offered and does not mention about the bandwidth demand itself [Hars2014]. Most of the studies make predictions (some of them using fitting procedures, extrapolations, regression analysis or equations) about the future demand or to estimate the traffic, either bandwidth or total volume. On the other hand, the fitting line in figure 20 is a good example of a situation where the future is strongly connected with its past and may imply this trend will continue (for how long?). Finally, it would be beneficial if more characteristics or properties of the fit are known such as the fitting error in terms of ARE or MAPE or a relevant indicator.

2.8 How much is the Internet Growing?

The study of the dynamic nature of the Internet has been given reasonable attention. From a more static point of view, nevertheless, progress is made below standard, given the continuously increasing traffic across different countries, ISPs, IXPs and the rapidly growing number of Internet users poses several geo-technical challenges and raises investment planning issues which must be known in advance. There are additional encounters on traffic engineering regarding the issues that affect the long term performance of networks rather than the short intervals based on dynamic assumptions. Of the main concerns was how much traffic growth there is on the Internet as a whole, as soon as it was realised that aggregate traffic has been increasing at high rates before the 2000s. We seem to have some explicit figures of the aggregating traffic but, on the other hand, some of the prediction attempts on their growth have been either inaccurate or totally absent. As opposed to the traffic collected at a single location to model the bursty and fractal characteristics for short or very short periods, indications of the growth of Tier-1 level networks, IXP points, wide area networks (WANs) and the entire Internet require long time measurements from multiple locations.

When the Internet was believed to grow rapidly, there was evidence that the WWW traffic alone was growing at exponential rates [Hub1999]. At the same time, K.G. Coffman and A.M. Odlyzko reported a rough doubling each year for the entire Internet, i.e. approximately 100% annual growth, and they predicted some time in 2002 the Internet traffic will overtake voice traffic, which was not the case until 1999 [Cof1999], [Cof2001]. Later, however – and as a matter of fact until today – the rate is still declining but the overall traffic continues to grow. Moreover, it was mentioned by Odlyzko that some press analysts believed the Internet traffic “doubles every three to four months, corresponding to annual growth rates of 700% to 1500%” [Odl1999, p.1870]. The author claims by that time AGRs of around 80-120% were realistic but were definitely not the ones that were usually cited by popular press accounts. In addition, Odlyzko demonstrated that such huge rates were misleading myths that originated from some press release talks in 1995 and 1996 [Odl2003]. The author continues with further similar reports from various sources of the “Internet doubling every 100 days” myth released until 2002 and concludes:
“The moral of this story (and the reason it is covered in so much detail) is that bad ideas are often remarkably difficult to discredit, even when there is extensive evidence against them” [Odl2003, p.7].

Regarding predictions from 2003 and onwards, it was believed by some investment companies and market research that annual growth will be declining down to 50-60% by year 2006 or 2007, or it could be also the case that growth will continue at a rate close to 2 [Odl2003]. In a previous publication in 2001, the same author reports "technological forecasting has a poor track record" [Odl2001]. After almost 15 years, the situation seems to be getting better, as more studies come to shed light to the picture of the past and the expected traffic growth.

The annual growth rate is calculated as the ratio of the aggregate traffic of a given year to that of previous year. Odlyzko made it clear that in the 1990s some reported "exponential" growth rates were wrong but a rate of around doubling year over year was realistic. In the decade of 2000s, the annual growth started to decay at a rate of less than 2. The annual growth rate has been calculated at 1.879 in period 2002 to 2007 [UoM6] and at 1.511 when another two years have been added to the calculations, i.e. the chronological timeframe 2002-2009 [UoM2]. In the same way as the more recent past is further considered, the mean AGR of the IP volumes of table 1 has been computed at 1.502. This suggests – and as a matter of fact confirms the previous assumption – that AGRs from recent years are highly likely to accommodate even lower rates when compared with the more distant past. This evidence is indeed correct as the respective AGR for the IP traffic in 2010 has been found at 1.401 and that of 2011 at around 1.36. Considering this consistent decline in the last years, are we to assume that traffic growth will continue with more or less the same trend over the next years?

2.9 Cisco's and Bell Labs high-level Studies

Apart from the important studies on Internet traffic already described, there are further research efforts targeted to the long term behaviour. In particular, an important study on future projections on fixed Internet, as well as on other types of traffic, is brought forward by Korotky (2013) at Bell Labs [Kor2013]. It is demonstrated that consecutive historical volume information cannot be precisely represented by using the mathematical logistic (sigmoid shape) function and it clearly illustrates that the trend is quite different than the logistic curve. Generally, logistic curves are often employed to characterize trends that exhibit significant growth at their early stages but later the trend tends to be smoother as it progresses in time [Wik2016]. The aforementioned function in [Kor2013] has been shown to have inadequate fitting properties when compared to historical Internet data but the author's proposed hyperbolic compound annual growth rate (CAGR) does indeed represent the history trend almost perfect. The accuracy of Korotky's proposed method makes his model a realistic tool to successfully indicate future traffic. The empirical CAGR values can be described with the following g(y) function for year y [Kor2013]:

$$g(y) = 10^{a} (y - y_o)^{b} \qquad (4)$$

Non-linear regression analysis has set parameters to be at approximately a = 3.02, y_o = 1993.9 year, b = −1.14 [Kor2013]. In addition, the report provides detailed projections for up to 2020 by application and markets segments and another important conclusion is that the volume growth decreases/is estimated to decrease over the decade 2010-2020 in terms of annual growth rate. Some of the results in [Kor2013] on fixed Internet traffic are presented in table 6.

Further world-leading research on long time Internet traffic is as well a subject by Cisco Systems. Cisco is a global leading organization which has significant contribution to projections in a variety of traffic aspect and in many other technological advances. Forecasting traffic figures is part of Cisco's work published in [Cis2012], [Cis2008], [Cis2008b], [Cis2013b], [Cis2014a] where important upcoming trends are observed. Their report in [Cis2014a] shows explicit details on global, fixed and mobile traffic projections by 2018 as well as other categories including estimates at different geographical regions. In a previous study, that of [Cis2012], volumes on global types of traffic in period 2011 to 2016 are presented when the original date of the report was in May of 2012. Furthermore, and 4 years earlier, Cisco had presented [Cis2008] and [Cis2008b] in June 2008, to make estimates in IP traffic volumes in the 7-year period 2006 to 2012 inclusive as shown in table 7. Later, nevertheless, there are some revised studies from the same company, one that was published in May 2013 [Cis2013b] and a further report about one year later in June 2014 [Cis2014a]. Specifically, projections can be seen in [Cis2013b, p.6] and [Cis2014a, p.6] on which there are figures of different types of traffic, including the IP and the fixed part. At a close inspection on tables 6 and 7, we are able to observe quite different forecasts. In particular, the numbers appear different when the common timeframes are compared separately for each table for the reports in [Cis2012], [Cis2013b], [Cis2014a]. But why do those projections come with fairly revised figures for those three years?

One reasonable explanation might be the constantly changing trend. Obviously, when each of those studies has been conducted each in different year, there may have been different assumptions and/or user trend as well which could have affected the investigation and, consequently, the estimation procedure. In the next tables 6 and 7, forecasts from Cisco are presented according to the two types of traffic; relevant projections from [Kor2013] are also included.

Estimated Fixed Internet Traffic in Year	Year of Report, [Source]				
	2012, [Kor2013] (forecast)	2012, [Kor2013] (fitted)	2012, [Cis2012]	2013, [Cis2013b]	2014, [Cis2014a]
2011	-	23,288	23,288	-	-
2012	33,049	32,177	32,990	31,339	-
2013	44,883	43,621	40,587	39,295	34,952
2014	59,096	58,127	50,888	47,987	42,119
2015	70,622	76,262	64,349	57,609	50,504
2016	80,562	98,650	81,347	68,878	60,540
2017	-	125,974	-	81,818	72,557
2018	-	158,976	-	-	86,409
2019	-	198,459	-	-	-
2020	-	245,281	-	-	-

Table 6: Global fixed Internet traffic estimates (PB/month)

Estimated IP Traffic in Year	Year of Report, [Source]			
	2008, [Cis2008, Cis2008b]	2012, [Cis2012]	2013, [Cis2013b]	2014, [Cis2014a]
2006	4,234	-	-	-
2007	6,577	-	-	-
2008	10,747	-	-	-
2009	16,296	-	-	-
2010	24,228	-	-	-
2011	32,983	30,734	-	-
2012	43,518	43,441	43,570	-
2013	-	54,812	55,553	51,168
2014	-	69,028	68,892	62,476
2015	-	87,331	83,835	75,739
2016	-	110,282	101,055	91,260
2017	-	-	120,643	109,705
2018	-	-	-	131,553

Table 7: Global IP volume forecasts (PB/month)

The revised information in the tables raises some critical issues. One issue would be to compare Internet volumes of the past with the studies that have been done earlier to make estimations for those volumes. A satisfactory answer may help us to understand the reasons of each year's revised predictions. Moreover, we might also be able to exclude some predictions and prioritize the possibility of some others to occur in the future.

It is commonly accepted that forecasting actual facts before those happen is a difficult task and that some level of error is indeed unavoidable. However, when making predictions on Internet traffic, it is highly recommended that a consistent methodology be followed using the criteria defined in the relevant chapter to minimize associated errors. Furthermore, there are two necessary additional conditions in order to maintain a low forecasting error:

(i) Accurate historical data.

(ii) Up-to-date user trends.

Condition (ii) may include some social and economic facts but those can be quite different from one year to another. Since those cannot be precisely speculated, any attempts on forecasting future aggregate volumes may appear different to the actual data once the latter become available. Estimations on future figures depend on the behaviour of Internet users and on technologies that are about to come on the market; this is as well a forecasting challenge. Therefore, the continuously fluctuating user trends might be a good reason as to why the recorded measurements of the worldwide IP volumes of table 1 come with different numbers than the projections in table 7 (1st column) and in 2011 (2nd column). By performing some detailed analysis, Cisco's associated forecasting error is relatively low if we observe the figures from the early years 2006 to 2008. A possible explanation might be that this interval can be interpreted as the "nearer" long run target, in which potential market trends are well known compared to the more "distant" long run. In contrast, the next three years that immediately follow, i.e. the timeframe in 2009 to 2011, belong to the far future and more "unpredictable" chronological interval which may incorporate huge levels of uncertainty. As an evidence, error rates in period 2009-2011 are indeed higher: the highest prediction error (notated as PrE expressed with the next equation) has been calculated at more or less 20% and has occurred in 2011. The relation uses the absolute difference of the real (actual, act) minus the predicted (forecast, for) value and the result is then divided by the former variable:

$$\mathrm{PrE} = \frac{|\mathrm{Vact} - \mathrm{Vfor}|}{\mathrm{Vact}} \mathrm{x}100\% \qquad (5)$$

Relation as expressed with (5), or in a similar way, is sometimes used to indicate relative errors. It can also define the forecasting accuracy in a relevant way such as in the work described in [Yid2009] and has, actually, the same meaning with the MAPE and ARE even if the latter two are expressed in different ways to comply with each study's methodology. Using again equation (5), the smallest error rate has been detected in the first interval – that of 2006 to 2008 – and has been computed at only 2.2% in 2007 and is almost negligible. Overall, the company's average computed prediction error considering the six year chronology is found at 11.56%. This rate is similar to the error range reported in [Tel2013], although the mathematical relation that was employed in that study is not given. In table 8, numerical results for the worldwide IP volumes forecasting errors of 2006 to 2011 are shown, according to the measurements in [Wik2015a] and the estimations in [Cis2008], [Cis2008b] as released in 2008. On the other hand, Cisco has predicted a fixed aggregate traffic at 31339 PB per month for 2012 while the actual figure was 31338 PB per month, which is of almost 100% precision, i.e. nearly 0% error. Equation (6) calculates the Historical Average Prediction Error, HAPrE(k), for k numbers of years for the traffic predicted vs. the actual historical traffic, where k = 6. Cisco's HAPrE(k) is at 11.56% and the more detailed figures are shown in table 8. The relation indicates the precision rate of forecasts over a certain timeframe.

$$\mathrm{HAPrE(k)} = \frac{1}{\mathrm{k}} \sum_{\varepsilon=2006}^{2011} \frac{|\mathrm{Vact}(\varepsilon) - \mathrm{Vfor}(\varepsilon)|}{\mathrm{Vact}(\varepsilon)} \mathrm{x}100\% \qquad (6)$$

Looking at results of table 8, there is a strong conclusion that forecasting attempts on the first three years timeframe are more accurate than those for the far longer term, provided all historical activity has been measured with precise figures. There is a considerable difference between the average error rate of 2006-2008 and that of 2009-

2011, as illustrated in table 8, suggesting that research on long term predictions must be limited to three years. Maybe one more year can be added but that should be only considered on special occasions, e.g. for very macroscopic investment plans. In this thesis a total number of four years estimates are usually presented and it is shown in core chapters that the three-year period is the optimum selection. Projections for the fourth year tend to be risky, however, and estimations beyond the proposed horizon are susceptible to high error rates. Several years or more can be only considered if there is a better understanding of the long term effect of user trends and only some general advice can be given such as projections using “guesstimates”. The latter term is used in a study in [Per2003] to indicate future outlooks in economics.

Year	Forecasting Error (Equation 6)	3-year Average Forecasting Error	6-year Average Forecasting Error
2006	6.06%	5.48%	11.56%
2007	2.2%		
2008	8.2%		
2009	13.05%	17.65%	
2010	19.9%		
2011	20%		

Table 8: Cisco’s HAPrE on aggregate IP volumes according to [Wik2015a], [Cis2008], [Cis2008b]

Jackson (2014) also raises some facts about Cisco’s reliability on future projections [Jack2014]. The author reports that Cisco has revised twice their initial forecasts on Consumer Internet traffic: both updated figures have been revised downwards and the maximum difference compared to the initial prediction is calculated at ~12700 PB per month [Jack2014]. This variation is definitely not to be neglected as the deviation in this case is relatively large.

Furthermore, revisions are also observed in [Cis2012] included in table 7, where some initial predictions for 2011 and 2012 come with different figures. As illustrated in table 7, the global IP volume for 2011 has been revised down to 30734 PB per month, where the initial prediction several years ago (in 2008) had been originally reported at 32983 PB per month [Cis2008], [Cis2008b]. Those slight updates are not a surprising fact considering the discussion in earlier sections. The variations of those two reports may be caused by the different trends at the time of their studies, as there is a chronological difference of four years between [Cis2012] and [Cis2008], [Cis2008b]. By performing the necessary calculations on error rates comparing actual measurements with predictions using relation (5), [Cis2012] revision in year 2012 has a forecasting error at only 11.8%, while this figure is increased to 20% in the initial predictions of 2008 as seen in [Cis2008], [Cis2008b]. If further error rates are to be calculated using all the available information so far of table 7 but also for the fixed traffic of table 6 as well, we can observe similar results in the common timeframes: most of the recent revisions tend to revise numbers downwards which may, in turn, accommodate lower error rates when compared to the initial older projections as soon as the actual measurements become available. This, again, confirms the uncertainty and the higher risk on prediction attempts for the longer term. It also justifies the need for up to date users trends and for setting prediction timeframes preferably to three years.

2.10 More Sophisticated Approaches on Long Term Predictions

Produced equations based on appropriate fitting of historical data have been further proposed. Maybe the greatest effort of such studies is performed by MINTS which have thoroughly analyzed recorded activity of 100 major traffic sources around the world, including the largest IXPs [UoM2]. Incoming and outgoing traffic from several consecutive past years is characterized by a fitting trend and described are the historical traffic aggregates using equations that are expressed as mentioned in the introductory chapter, but more specifically are of the following form:

$$y = 10^{bx + d} \rightarrow y = 10^{d} \cdot 10^{bx} \quad (7)$$

The London Internet Exchange (LINX), one of the largest IXPs, has an average traffic of 6.400e+10 bps as observed between 4 February 2002 and 21 August 2009, an annual growth rate at 1.5971 for the total traffic and is characterized by the following equation (8), where x is the day and y the traffic in bps, and its data with the fitting curve are as shown in figure 21 [UoM7]. All details for data, relations and analyses of this massive study can be found at the MINTS website.

$$y = 10^{3.5082} \cdot 10^{0.0006x} \tag{8}$$

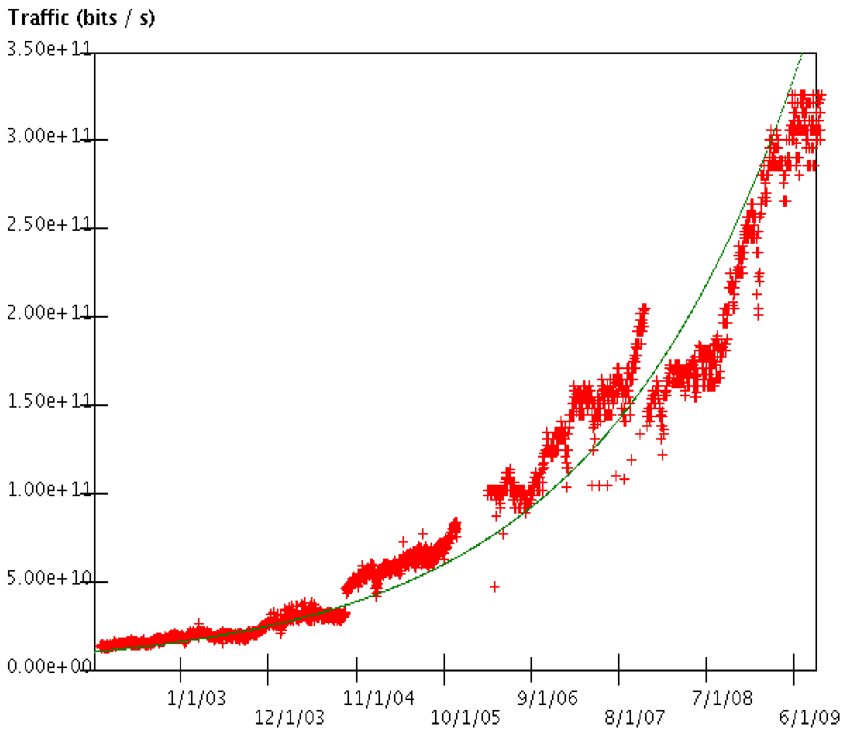


Figure 21: Fitted traffic data for the LINX [UoM7]

Another study similar to MINTS, as referenced by Labovitz et al (2010), looks for an exponential fit of the following expression, where y is the traffic in bps and x is the day [Lab2010, p.84]:

$$y = A \cdot 10^{Bx} \quad x \in [1, 365] \tag{9}$$

The fitted curve over 365 daily collected traffic traces from May 2008 to May 2009 can be seen in the following figure:

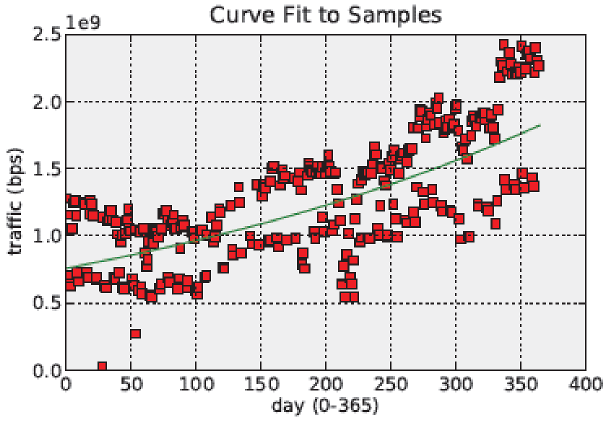


Figure 22: Curve fit over a year's traffic by an anonymous provider [Lab2010, p.86]

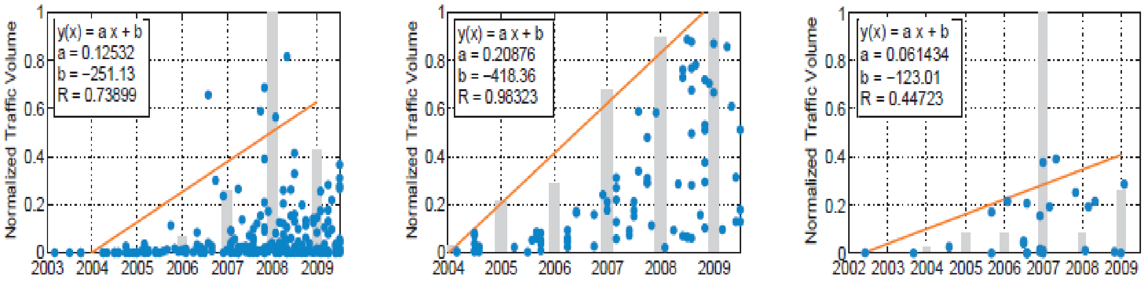
In the same study, calculated is the total traffic volume for May 2008 at 9 Exabyte (EB), which matches with Cisco's estimates and is also compared with MINTS figures [Lab2010, p.84-85] in the next table:

Estimate	110 ISPs	ISP Survey	Cisco	MINTS
Traffic Volume Per Month	9 exabytes	N/A	9 exabytes	5-8 exabytes
Traffic Annual Growth Rate	44.5%	35-45%	50%	50-60%

Table 9: Labovitz et al results for May 2008 (first column) [Lab2010, p.85]

Finally, more characterization studies are reported but specifically for mobile network traffic and according to device types and applications by Shafiq et al (2011). Aggregate and separate devices' traffic have been observed for 1 week in which diurnal characteristics are present [Sha2011, p.308] similar to the sinusoidal-like shape of weekly and day-to-day traffic mentioned in previous sections. At the same time, of more importance are the traffic volumes generated by 3 types of mobile devices over a number of consecutive years for which a regression line is plotted for each type's historical traffic [Sha2011, p.309] demonstrated in figure 23. The general expression of the regression equation is of the form:

$$y(x) = a \cdot x + b \qquad (10)$$



(a) Smart Phone A (b) Smart Phone B (c) Wireless Modem W

Figure 23: Regression lines for mobile devices trend characterization [Sha2011, p.309]

The equation in figure 23.(b) characterizes the trend line quite accurately. However, most of the methods employed for long term modeling and prediction, are observed to have some level of dispersion at the characterization process which has been not clearly defined and can therefore lead to large fitting and even forecast error rates. In addition, the methods described as being more static do not seem to report the associated fitting error such as for figures 21, 22, 23 even if different techniques are employed in those studies. In this thesis, fitting errors are minimized to very low levels in order to produce suitable mathematical formulas to predict traffic volumes with precise figures. The following chapter takes into consideration these peculiar issues and demonstrates an effective methodology for the long term analysis and projections of network traffic.

CHAPTER 3

Methodology

"All is Number.
Number rules the Universe"

- Pythagoras

The proposed method for long term Internet traffic modelling and forecasting is presented in this chapter. Based on four distinct conditions, rigorous characterization of massive historical measurements can successfully indicate future figures using novel mathematical formulae.

3.1 Introduction

As outlined, a considerable part of relevant research concentrates on popular statistical time series models, neural networks and analysis of the dynamics of the collected traffic traces. At the same time, another important part advances to more static techniques and use less dynamic assumptions making it more relevant to this thesis' methodology, albeit with a different approach. The materials on which this investigation is based on are the collected actual historical data of available Internet volume figures from various traffic sources as well as the evolution of the number of Internet users worldwide. Furthermore, the methods that have been used herewith are to reveal how the numbers of the time series seen in this history traffic are connected to each other. Certain connection properties have been observed over continuous chronological intervals that can be represented with appropriate fitting curves which, in turn, can indicate the growth of the corresponding traffic volumes for the future. For most of the data, there are hidden patters and these have been successfully detected in chronological order.

Subsequently, it has been further observed those patterns can be described with mathematical equations which have never been proposed before. In most of the reported cases in core chapters, the proposed formulae (i) encompass prominent fitting characteristics with the values from respective historical measurements and (ii) are expected to provide very good prediction results for the next years with an expected average prediction error at far less than 10%. Namely in the case where some new traffic data are already released, the hereby proposed methods have lower prediction errors than projections coming from other research bodies, averaging a rate of less than 5%.

3.2 Selecting Appropriate Traffic Data: The 4 Criteria

Predicting global or regional traffic for the next few years, either fixed or IP, means there are adequate traces from several previous years which can form the basis of high-level studies for successful future projections. If data are not sufficiently collected or if they are just a small part of the total sample, prediction attempts may result in excessive error rates. In this thesis in order to successfully forecast traffic figures for the next years, “sufficient” or “adequate” can be defined as the following two criteria:

***Criterion 1**:* All available Internet traffic from at least four - but ideally more than four - consecutive years of the past must be taken into consideration to form the time series data. For example, to make estimations of the total volume for years 2014, 2015, 2016 we need at least the traffic history in years 2010, 2011, 2012 and 2013. More efficiently, nevertheless, extensive traffic history for up to more than several years would be ideal to reveal any consistent long term trends, but this is not always possible.

***Criterion 2**:* The activity must come from a network of which traffic has either an impact on the total global flow or expands to a large geographical range. Therefore, good examples of appropriate networks are major backbones and large Internet exchange points such as the Amsterdam and London IXP. In contrast, small samples of traffic or measurements captured at random chronological intervals are not suitable. As such, traffic across a local node or a community (e.g. a University campus), the flow coming from a big city or even a whole country but with gaps in measurements are all excluded and therefore not considered for the purposes of this research.

Pattern detection can be only applied to data for large areas and with complete long term historical information to be defined as adequate, thus 1 and 2 must be satisfied. Modeling historical trends with an arbitrary pattern of some absent values is possible [Ban2010], but cases in the present studies exhibit different peculiarities and have other types of constraints. Also, studies in [Zhan2009] have shown that enlarging data does not really enhance prediction accuracy. In this thesis, however, there are different assumptions for making predictions, thus enlarged and representative samples of pertinent historical data are a prerequisite.

Furthermore, there are additional conditions that must be satisfied as well and these are more relevant to the quality of the available information, rather than the quantity issues mentioned in criteria 1 and 2. The suitability of the historical Internet volumes is the key to extract the connection properties of the pertinent data through careful observation as numbers progress over years in chronological order. These pure values must have the following properties and are defined as criteria 3 and 4:

Criterion 3*:* Consecutive historical traffic volumes are only considered within the last ten years to accord with trends and must constantly increase in time, i.e. total traffic V for a given year Ɛ must exceed V of previous year:

$$V(\mathcal{E}) > V(\mathcal{E}-1), \qquad \mathcal{E} > 2004 \tag{11}$$

Criterion 4*:* Their increasing values will ideally have smooth progression properties as they advance over time, i.e. all numerical values would preferably have no sudden peaks, spikes or irregular fluctuations. If such irregularities are present, then statistical indicators such as standard deviation, RMSE and/or fitting error over subsequent years will preferably incorporate low values; otherwise there is a risk of coming up with inaccurate predictions at the later stages.

Condition in 3 is of outmost importance and only then are these studies considered. Indeed, all the collected traces imported in the thesis satisfy this demand on a global and more local basis. Restriction Ɛ > 2004 is to ensure that included are only the latest traffic trends and for the years of which traces are available according to the four criteria specified on the whole. In addition, the requirement described in the 4^{th} criterion is to define the success rate of the fitting procedure and, consequently, the curve/line fitting error. The quality of the combination of 3 and 4 will determine how easy or difficult it is to detect the patterns in the available successive numbers and then form a suitable relation. In any case, the information and methodology that have been used to conduct this research satisfy all four conditions 1 to 4 and, as such, studied are only those traffic traces which meet them in full. Criteria 1, 2 and 3 are straight forward as opposed to 4 which is more flexible and accompanied by some level of arbitrary calculations. At the same time, the quality of the mathematical relations to be derived from the fitting and pattern detection procedure must be guaranteed prior to making numerical experiments and predictions for the future; full achievement of all criteria 1 to 4 are almost definite to guarantee excellent results.

However, producing reliable equations in any scientific field is – apart from challenging – a difficult task and a considerable level of difficulty does also apply to these studies. The use of straight-forward equations are important to all scientific fields and, here, the intention is to produce simple and practical relations and to establish them in Internet traffic forecasting. At this point it must be mentioned that no software was used in order to trace any patterns or to produce the mathematical equations from all available data sets. Although there are available computer programs that can manipulate large quantities of samples, the results obtained in all chapters rely exclusively on my own intelligence, intellectual and observational abilities. Only standard programming languages have been used and only for the purpose of saving time on the large scale numerical experiments and calculations. To the best of my knowledge no software is able to produce directly these findings and formulae to the extent it has been accomplished and described herewith.

3.3 Dynamic versus Static-Based Predictions

The term “static” or “non-dynamic” shall be referred in the thesis as the basic approach for the proposed methods. As reported in [Klo2004], dynamic predictions are based on previously repeated forecasts, i.e. when a forecast number is produced it is then referenced to form the next figure and so on. On the other hand, static methods perform predictions according to already available data which require actual historical numbers [Klo2004] and a similar method is used exclusively in the thesis.

Static approaches are not hitherto unknown. Other than the relevant studies already described, there are some similar-like approaches in different scientific topics, which represent some of the state-of-the-art studies in their fields. In tumor growth modelling, a parameterized exponential model [End2014], best-fit curves for two models [Mar1996] and regression lines [Ben2014] are each presented for selected purposes. In economics, evaluating a static factor model is included in [Che2007] to predict the Gross Domestic Product (GDP) in Canada. Another report on forecasting the German GDP uses three different models, including a static. The study, which comes from the “Deutsche Bundesbank”, is based on 124 series of data from 1978 to 2004 and points out that none of the dynamic factor models shows better prediction results than the static [Sch2005].

3.4 Excluding Certain Traffic Collections

There are traffic samples which meet all prerequisites from the previous section and some others that do not. All collections used in the thesis satisfy the necessary conditions. Historical measurements which do not meet all criteria are not necessarily to be omitted from studies in general, but it is essential that this investigation is based on reliable evidence in order to make successful predictions when these will be compared with the actual data once they are released. Performing studies on not so consistent information might result in error percentages from 10% to 20% or more. Even if the range of 10-20% seems acceptable – and as a matter of fact is already the case for many related investigations – it is not preferred for the present studies. The contribution of this thesis must be achieved to the maximum and this suggests forecast errors less than 10% on average and ideally below 5%.

Unsuitable historical traces can produce dispersed figures at the fitting stage and this can lead to magnified forecasting errors. The example of table 10 is the incoming and outbound aggregate traffic that has crossed the Amsterdam IXP in 2014. We can observe the traffic generally increases from the beginning to the end of the year for both incoming and outgoing (and consequently for their totals), but in between certain months there are significant drop offs. Modeling any data set that displays seasonal variations is susceptible to significant deviations at later study stages and should maybe assigned to more dynamic techniques. Therefore this sample may not be suitable to form a reliable basis for predictions and cannot be used for either fitting, relation forming or projection purposes. However, if all numbers of the data set are added together to represent the totality of volume for 2014, then all relevant aggregate volumes from past years of the same IXP can be merged into one table in chronological order. The new table will have the total volumes of the traffic from several consecutive years of the past, e.g. from 2009 to 2014, to predict figures for years 2015 to 2018. The latter is indeed a core project in this thesis and is presented later.

AMS IXP traffic totals, year 2014 (TB/month)		
Month	**Incoming traffic**	**Outgoing traffic**
1 (Jan)	577990	577835
2	517598	517406
3	570113	570014
4	548569	548550
5	591496	591449
6	570756	570872
7	571791	571738
8	583672	583613
9	604635	604479
10	663548	662459
11	663009	662547
12 (Dec)	679438	679254

Table 10: Amsterdam IXP: variations on monthly historical volumes [Ams2014]

U.S. Internet backbone traffic by year	Traffic in terabytes (TB) per month
2006	450,000 – 800,000
2007	750,000 – 1,250,000
2008	1,200,000 – 1,800,000
2009	1,900,000 – 2,400,000
2010	2,600,000 – 3,100,000
2011	3,400,000 – 4,100,000

Table 11: Estimated backbone traffic in USA [UoM1], [UoM5]

Further examples that can possibly lead to huge prediction errors are measurements given in broad ranges or traffic activity compiled into a single graph without precise figures, as shown in table 11 and figure 24 respectively. Table 11 may be a good indication of what is to be expected for 2012 and later, but no constructive investigation can be conducted to detect patterns or produce fittings. It is quite obvious that those data do not display a specific traffic pattern in terms of accuracy for either prediction or modelling, mainly because of the wide range of the numbers they are given. Although traffic uncertainty is relatively high, the data in the table could be a good start in revealing patterns but these would be only based on the lower and upper limits of the values of each year as the latter increases to 2011. Projections using this method would again produce some specific ranges and estimates would not be accurate, even if this method is safer due to the increased probability defined by the wide range of the numbers. The same applies to extrapolating figures by producing curves or lines that fit into the area specified by the lower and the higher levels of the numbers. In contrast, detecting patterns in the progression properties of standard numbers rather than in the properties of dispersed ranges is expected to lead to better estimations on future values. The convenience of forecasting traffic volumes within excessive ranges cannot be regarded as producing “safe results” because networking and investment companies need more precision when it comes to their future plans: they need projections that come with fixed numbers or at least with some very narrow ranges.

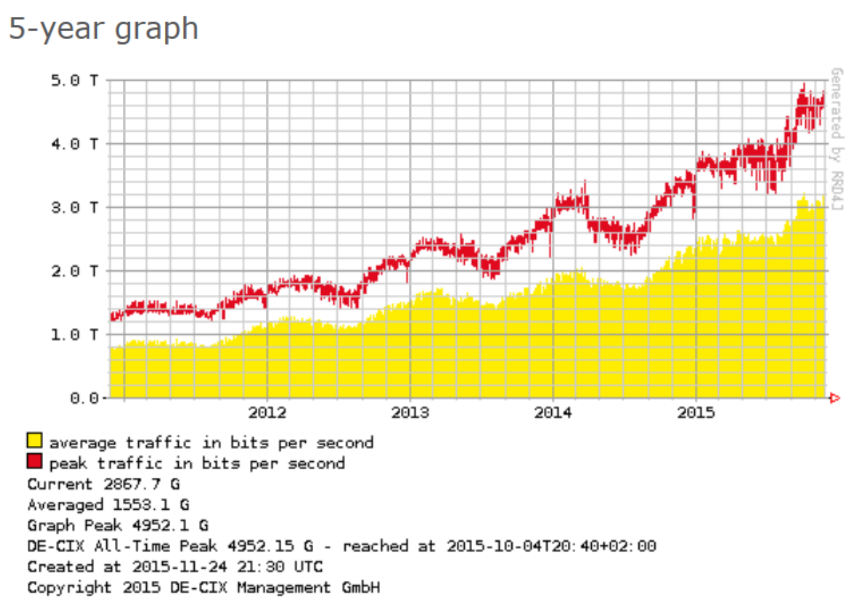


Figure 24: Traffic exchanged at the DE-CIX in Frankfurt [Dix2015]

The graph in figure 24 comes from the "Deutscher Commercial Internet Exchange" (DE-CIX) in Frankfurt [Dix2015] and is certainly useful, especially the average traffic (yellow) as opposed to the peak activity (red) which exhibits medium-level fluctuations in 2014 and 2015. The former meets all specified criteria but obviously there is absence of figures. At close inspection, one might be able to extract all numbers as they progress from 2012 to 2015 but these would be within certain ranges – even narrow – or they would come with a standard level of tolerance. Any lack of precision may not be an important issue for the general public's information but for high-level studies accurate figures collection is strongly advised.

3.5 Suitable Historical Measurements

The desired level of explanation of historical measurements can lead to precise estimates and table 12 is an explicit example that meets all conditions. The numbers have hidden properties and this pattern always depends on the value of each previous number. In other words, the pattern can be well represented with an equation which takes the relation from the volume of a given year $\varepsilon-1$ and performs calculations to assign the new value to the volume of year ε. Any number on the right hand side of the table depends on its previous value, i.e. the volume information is always related to that of previous year and can be expressed with a mathematical equation including variable ε as a separate parameter. The numbers of the table have been observed to produce a hidden model to characterize the traffic and the fitting attributes, which is able to further indicate the future values in advance with a low associated error. In broad format, the equation is expressed as:

$$V(\mathcal{E}) = [V(\mathcal{E}-1)]^{P} \qquad (12)$$

$V(\mathcal{E})$ refers to the total traffic volume we want to predict for year $\mathcal{E}$, which clearly depends on the available historical volume $V(\mathcal{E}-1)$ from previous year. Exponent P is to be formed according to the investigation case in each chapter and is a more complex parameter that includes variables and constants defined at the fitting and pattern detection process. The same idea is as well to be applied to all history traffic data used in this documentation, including further tables with several years of recorded traffic from large and consecutive data samples.

The format in (12) of the proposed relation is similar to the MINTS and Korotky's equations format and to other related studies that use an exponential form to predict or fit the traffic as a function of the year (or the day where applicable). In addition, the rather general appearance of equation (12) is to be altered accordingly in subsequent chapters to comply with the fitting and prediction peculiarities of each purpose. In this way, a further advantage is the minimum effort that will be required in the future if and when equations need to be updated according to the trends.

Global Internet Protocol (IP) Traffic (PB/month)	
Year ε	**Total measured volume**
2005	2,426
2006	3,992
2007	6,430
2008	9,927
2009	14,414
2010	20,197
2011	27,483

Table 12: Historical global IP volumes [Cis2013], [Wik2015a]

Last but not least, the selected timeframe for predictions has been limited to three years at maximum due to the uncertainty of future trends as these can unpredictably change at any time. A further fourth year has been included in most chapters to verify that even an additional year beyond the suggested 3-year period is susceptible to increased error rate. It must be realized that focusing on the next few years, rather than too macroscopically, has a lower risk of failure and this issue has been successfully pointed out in the respective part of the literature review. On the other hand, nearer time estimations along with all four aforementioned conditions, strongly suggest that the trend is likely to remain stable resulting to more accurate estimations. For the present studies, the selection of small chronological forecasting periods of either three, or four years at the most, is expected to be the optimum choice. At the same time, it is recommended that revisions and necessary updates of all proposed equations in this thesis be conducted every three years. Finally, the proposed model implies that any future activity for a specific geographical range depends on the past activity for the same region, as long as all essential prerequisites are satisfied as discussed. In other words, the successful model candidate can be described with the following sentence:

If we possess a big and representative set of successive information from the past that follow a pattern which can be expressed with a relation, then we can count on reliable predictions of future traffic.

Through the next chapters, the accuracy of the proposed model is demonstrated and, as pointed out in the literature review, errors at less than 10% mean accurate predictions. Also, Borzemski et al (2011) state that in particular a MAPE measure below 10% is a very good indicator of prediction results [Bor2011], which is the case in these studies as well. The performance of all proposed models will be evaluated as soon as actual data for the targeted timeframe become available and this shall be indicated in respective chapters where applicable. At the same time, fitting statistics of historical traffic demonstrate the abilities of the suggested formulas. Producing appropriate relations for successful forecasts starts immediately in chapter 4.

CHAPTER 4

Analysis and Prediction of Aggregate Traffic across IXPs:

The Case of the Amsterdam Internet Exchange Point

"Necessity is the mother of invention"

- *Plato*

This chapter introduces the reader to a novel method for characterizing and estimating traffic according to historical measurements by producing a new formula. The study is performed on one of the largest gatherings of traffic volume in the world for which there are sufficient recorded traces, the Amsterdam Internet exchange point. The proposed equation has successful results on predictions for aggregate traffic in 2015.

4.1 Share of Internet Traffic by Internet Exchange Points

Internet eXchanges or Internet eXchange Points (IXPs) are large local networks that allow peering between other parties such as carriers, ISPs and other networks. IXPs provide connection to other large networks directly rather than through other infrastructures or third-parties from other locations. Internet exchange points are a major part of the Internet infrastructure and they are main contributors in the evolution of the Internet topology [Ahm2010]. A considerable number of IXPs exist on the Internet and in all geographic continents around the world. Internet exchanges are traffic sources that account for nearly all bandwidth of the Internet, however there are countries that still lack an IXP and need to import bandwidth from other countries that do have IXPs [OECD2013]. Holland, for instance, is a country that consumes 50% of the bandwidth that its IXPs produce and is a major bandwidth exporter [OECD2013]. Internet exchange points grow fast on a global scale in terms of total number and especially in overall bandwidth capacity, with most of the total activity coming from our region, Europe, as shown in table 13. Full details of IXP statistics for a list of countries can be found in the relevant report available from the Organisation for Economic Co-operation and Development in 2013 [OECD2013].

	Internet Exchange Points				Domestic Bandwidth Production			
Region	**Apr 2006**	**Apr 2011**	**Net Change**	**Percent Change**	**Apr 2006**	**Apr 2011**	**Net Change**	**Percent Change**
Africa	18	22	+4	+22%	159M	3.22G	+3.06G	+1921%
Asia-Pacific	60	76	+16	+27%	636G	1.13T	+497G	+78%
Europe	85	137	+52	+61%	797G	6.28T	+5.49T	+688%
Latin America	20	34	+14	+70%	4.81G	62.3G	+57.4G	+1193%
North America	76	88	+12	+16%	121G	885G	+764G	+634%
Total	**259**	**357**	**+98**	**+27%**	**1.56T**	**8.37T**	**+6.81T**	**+81%**

Table 13: 5-year growth figures of IXPs [OECD2013, p.54]

In table 13 we can observe the number of IXPs and that their respective bandwidth offer have grown in all continents. Latin America is the fastest growing in terms of total number of IXPs, while Africa has the largest percentage growth in regional bandwidth production. Although Africa’s figure at 159M in 2006 and 3.22G in 2011 is small compared to other regions, we may further expect high levels of growth at those locations in the future. The same trend may be the case for Latin America as well, since both of them seem to have high growth rates not only caused by IXP traffic but for their total global figures too as presented in the next chapter.

In spite of measuring the Internet as a whole infrastructure, there is not much effort on the more localized Internet [Res2012]. A study by Ahmad et al (2011) reports almost 44000 peering links at various IX points were missing (invisible) at the time of another study conducted, as referenced therein [Ahm2011]. Of even more important note is the fact that nine large IXPs in the world are responsible for 43% of the total traffic, including the one in Amsterdam [Ahm2012]. The following table illustrates important figures of the total flow and the number of members for each of the nine IXPs in three different continents.

Region	Name	Prefix range	Traffic	No. of participants	No of IXP paths found
Asia-Pacific (AP)	Japan Internet Exchange	210.171.224.0/24	251G	85	76187
	Hong Kong Internet Exchange	202.40.160.0/23	193G	105	27269
	Korea Internet Neutral Exchange KINX	192.145.251.0/24	86.2G	42	4428
Europe (EU)	Deutscher Commercial Internet Exchange	80.81.192.0/22 80.81.200.0/24	1.85T	325	431187
	Amsterdam Internet Exchange	195.69.144.0/22 195.69.145.0/24	1.55T	484	422521
	London Internet Exchange	195.66.226.0/23 195.66.224.0/23	1.25T	407	336627
USA (US)	Equinix IBX Ashburn	206.223.137.0/24 206.223.115.0/24	305G	72	143431
	New York International Internet Exchange	198.32.160.0/24	191G	137	44022
	Seattle Internet Exchange	206.81.80.0/23	89.6G	151	74368

Table 14: Statistics from popular IXPs as of January 2012 [Ahm2012, p.622]

The top three of the exchanges are located in Europe and their behaviour in terms of total traffic, fitting curve and incoming/outgoing equation has been already studied by the MINTS as updated in September 2009 [UoM2]. In 2015, however, there are detailed traffic volume figures for the Amsterdam exchange of which historical measurements shall indicate future growth as explained in the next sections.

4.2 The Amsterdam Internet Exchange Point: Numerical Properties and Patterns in Historical Traffic Data

All recorded traffic that has crossed this large peering network since 2001 is available from [Ams2015]. The historical data start from July 2001 until August 2015 and for the research purpose investigated are years 2005 to 2014, to comply with the constraints of equation (11), criterion 3 in chapter three, and due to the incomplete data for 2015 when this study began. The restriction of relation (11) is to consider a maximum of 10 years of recorded history, mainly to keep up to date with the trends of the more recent past, but the exact number of years is to be determined by all four criteria justified in the methodology.

All monthly traffic volumes of the past are included at [Ams2015] for the incoming and outgoing traffic and at this very first stage all monthly data of each year have been merged and imported in a spreadsheet to form the yearly figures. After adding them up, a new table with the aggregate volumes has been produced for each of the years 2005 to 2014 inclusive, which are plotted into an X-Y coordinate graph. This phase is the most important in the sense that it must be made clear which of the four criteria are satisfied as exactly described. Obviously, the first three conditions are met while the 4th criterion has some peculiarities. The results for the yearly historical data from 2005 to 2014 from the Amsterdam IXP are summarized:

1st criterion: confirmed (more than four years of historical data)

2nd criterion: confirmed (the aggregate volume samples come from a large geographical region across West Europe)

3rd criterion: confirmed (yearly traffic figures are constantly increasing from 2005 up to 2014)

4th criterion: partly satisfied – years 2005 to 2008 have produced medium level of spikes that affect the smooth properties of the graph, which increases the difficulty at the pattern detection process. Nevertheless, the rest of the traffic volumes from 2009 to 2014 have smooth properties.

For dynamic modelling, the presence of spikes may not be an issue but using a more static approach may lead to significant fitting and forecasting error rates. As already emphasized, the preferred option for this thesis is an average prediction error of less than 10% and ideally lower than 5%. Therefore, traffic data from period 2005 to 2008 will be excluded and considered is the timeframe 2009-2014 to proceed to the next stage. The exclusion of the aforementioned period does not affect the procedure as the new data have been again verified against all criteria which are now met in full. The new figures to be investigated are given in the following table in Terabytes (TB).

Traffic that has crossed the Amsterdam IXP			
Year Ɛ	**Total volume (TB in year Ɛ)**	**Monthly average volume (TB/month)**	**AGR**
2009	3498294	291525	N/A
2010	4913330	409444	1.404
2011	6430632	535886	1.309
2012	8277665	689805	1.287
2013	11156521	929710	1.347
2014	14282831	1190236	1.280

Table 15: Aggregate traffic, as compiled from [Ams2009] – [Ams2014] with respective AGRs

Although traffic volumes in 2009-2014 increase year after year, the annual growth figures confirm the declining growth rate of the Internet traffic and, here specifically, of the Amsterdam IXP (table 15). The information for the monthly traffic will be analyzed to detect any existing numerical patterns in numbers as these progress in chronological order. Equation $V(Ɛ) = [V(Ɛ-1)]^P$ from previous chapter is now used and the format is accordingly modified to indicate traffic at the Amsterdam Internet exchange point expressed with the following relation:

$$AMS.IXP(Ɛ) = [AMS.IXP(Ɛ-1)]^P \tag{13}$$

The selected monthly average values 2009-2014 from table 15 are substituted into equation (13). Values of all respective years Ɛ will be expressed as a function of volumes of previous years (Ɛ−1) and will form the relations, which are to reveal the values of exponent P_i in each pair. After substituting all volumes from table 15 with the actual numbers, we get the next set of expressions:

$$AMS.IXP(2010) = [AMS.IXP(2009)]^{P1} \rightarrow 409444 = 291525^{P1} \tag{14}$$

$$AMS.IXP(2011) = [AMS.IXP(2010)]^{P2} \rightarrow 535886 = 409444^{P2} \tag{15}$$

$$AMS.IXP(2012) = [AMS.IXP(2011)]^{P3} \rightarrow 689805 = 535886^{P3} \tag{16}$$

$$AMS.IXP(2013) = [AMS.IXP(2012)]^{P4} \rightarrow 929710 = 689805^{P4} \quad (17)$$

$$AMS.IXP(2014) = [AMS.IXP(2013)]^{P5} \rightarrow 1190236 = 929710^{P5} \quad (18)$$

All numbers are expressed in TB/month and obviously index i = 5 (maximum). By solving equations (14) to (18) according to P1 to P5 respectively, we make use of the following power-logarithm relation and the logarithm identity property defined as:

$$\chi^{\psi} = \omega \leftrightarrow \psi = \log_{(\chi)}\omega \quad (19)$$

$$\log_{(\chi)}\omega = \log_{(2)}\omega \,/\, \log_{(2)}\chi \quad (20)$$

Relation (19) will be used to reveal exponents, while (20) converts any logarithm base to the desired in the Java programming language, which is the software to be used for the large-scale numerical experiments. Then from equations (19) and (20), P1 to P5 have been calculated as shown in table 16 expressed to 6 significant figures:

Relation	**Value of P_i**
$409444 = 291525^{P1}$	1.026995
$535886 = 409444^{P2}$	1.020826
$689805 = 535886^{P3}$	1.019140
$929710 = 689805^{P4}$	1.022200
$1190236 = 929710^{P5}$	1.017976

Table 16: Equations (14) to (18) with their P1 to P5 respectively

The next and most critical stage is to detect hidden patterns in all P variables as revealed in table 16. Looking carefully at the second column of the table, all values generally decrease as P_i increases with the exception of P4 which can be defined as a "small" spike. This issue can be overlooked as long as there is a satisfactory progression property detected from P1 towards P5 and provided that a small fitting error exists (to be calculated later). For all P1 to P5, the ideal situation would be a fixed number to be subtracted starting from the first with the aim to approach P5 at the last subtraction. If there was such a fixed number, say A, then we would get the following set of relations:

P1 – A = P2

P2 – A = P3

P3 – A = P4

P4 – A = P5, which is of generic form:

$$P_i - A = P_{i+1} \tag{21}$$

But since (21) cannot be applied, the next step would be to detect a pattern relation by adding one parameter (either fixed or variable depending on the situation) to each of the variables we already have, which would be of the following expression:

$$(a \pm P_i) - (b \pm A) = (c \pm P_{i+1}) \tag{22}$$

Factors a, b, and c can be divided into more arithmetical operations including additional variables and may affect the quality of (22) in a negative way if the wrong values are assigned to a, b, c. However, using equation (22) is the key to approximate P1 to P5 successfully, albeit with a small error. This error is to be defined as the fitting error, later at the fitting procedure. At this point, extensive numerical experiments will be carried out to set A, a, b, c to a plethora of operations (at least in the order of millions) and values that only calculation software is able to perform. In this thesis, those extensive experimentations are performed with the Java programming language to iterate complex calculations within loops using numerical programming. Those large-scale experiments will be performed using an extensive range of numbers assigned to A, a, b, c. The combinations of their values will be evaluated against the actual numbers of table 16 and the newly formed values will later define the fitting error. The aim is to find the combination of values A, a, b, c and operations, which incorporate low errors and selected will be the lowest compound average error considering all P_i. As such, repeated experiments have set the new P_i's to be as accurate as possible compared to the actual, but at the same time they must have a low deviation compared to the P_i's of table 16. On the other hand, calculations must reveal new values to have a good decreasing pattern as this will be used to form the final format of the proposed novel formula.

Indeed, results have indicated the average deviation rate to be at an exceptionally low rate compared to those of table 16 and has been calculated at below 0.4% (<4‰) which is totally negligible. Table 17 reveals their new values, which are expected to accommodate a low fitting error as a consequence of a low deviation and will lead to successful traffic predictions. Obviously, each P reduces by 0.002 related to its previous, which is not a difficult task to form the exponent of the equation.

P_i	New values
P1	1.024
P2	1.022
P3	1.020
P4	1.018
P5	1.016

Table 17: P1 to P5 alternative figures revealed at the pattern detection stage

4.3 Traffic Data Fitting

Proceeding to the next stage, the newly formed data are to determine the fitting error rate of the historical traffic. At this point it must be mentioned even if very low fitting errors are achieved, they are likely (but not definitely) to magnify the forecast error rate some time when traffic figures of the future become available to compare them with the proposed predictions. Therefore it is essential to come up with considerably low errors at this present stage. The next table summarizes the proposed fitting procedure and statistical figures; the respective error is computed using formula (23):

$$\text{Fitting Error } (\%) = \frac{|\text{AMS.IXP(actual)} - \text{AMS.IXP(fitted)}|}{\text{AMS.IXP(actual)}} \cdot 100 \tag{23}$$

Year ε	Proposed P	Fitted AMS.IXP(ε) (TB/month)	Actual AMS.IXP(ε) (TB/month)	Fitting error (%)
2010	1.024	394301	409444	3.69
2011	1.022	544080	535886	1.53
2012	1.020	697676	689805	1.14
2013	1.018	878665	929710	5.49
2014	1.016	1158353	1190236	2.68
Average fitting error				**2.906**

Table 18: Fitted traffic vs. actual for the Amsterdam Internet exchange point

The calculated mean fitting error at 2.906% is not exceptionally low but is indeed within a very good acceptable range and the actual historical data have a good match with the proposed fitted. Another important achievement comes at the pattern detection trials which, out of millions of operations, seek to select an optimum range of P_i's but at the same time reveal a consistent and convenient numerical decrease of each P. Indeed, P_{i+1} is always subtracted by 0.002 related to each P_i.

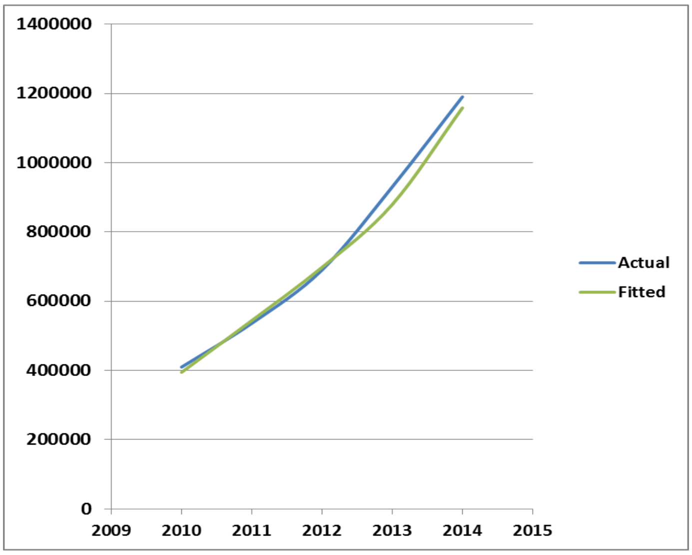


Figure 25: Actual and fitted traffic

As shown in the graph (figure 25), the fitted representation is in line with the progression shape of the historical activity. The selected actual data of 2009-2014 have smooth progression over the selected timeframe and this attribute is well captured by the fitted traffic. Should the long term trends remain the same as with those in the past, or behave very similarly, it is expected that forecasts on future traffic will follow the same regression shape and be almost identical with the suggested fitted data.

4.4 The Proposed Equation

The next stage is to form a widely accepted and parsimonious formula. The basic format of the promising relation will be that of (13) combined with the new values of P and as a function of year Ɛ. This investigation part is of high importance as well but is more difficult than detecting patterns, primarily because variable Ɛ must be included in the exponent P. Furthermore, Ɛ has to be an integer representing the year and must bridge the fitted historical values with the successful future figures, which brings more difficulty to form an appropriate equation. However, performing some basic numerical analysis on the numbers of table 17, it is easy to observe a steady decrease of 0.002 to all P values. With regards to P1, the latter figure is multiplied by 2 as P1 increases to P3, by 3 as P1 increases to P4 and so on. This pace combined with the year increasing +1 from 2009 to 2014 introduces a new method of presenting progression properties of different patterns. It is essential to bookkeeping those properties, observe the way they progress in time as a function of parameter Ɛ and then form suitable relations according to these. Consequently, after another set of extensive experiments which include all necessary information, the pattern relation has been verified with further numerical programming. The empirical form of the new proposed equation is expressed with (24):

$$\mathrm{AMS.IXP}(\varepsilon) = \mathrm{AMS.IXP}(\varepsilon - 1)^{\frac{24-2(\varepsilon-2010)}{1000}+1} \tag{24}$$

Year ε in the exponent is always an integer. This equation is simple, straight-forward and is a complete representation of the fitting data, as discussed, and of the predictions to be made as a function of the corresponding year. The fitting data are of period 2010-2014 and the forecast horizon has been selected to four years ahead, i.e. 2015 to 2018 inclusive. Thus, the following restrictions must be taken into account for calculations:

$$2010 \leq \varepsilon \leq 2014, \text{ for fitting purposes} \tag{25}$$

$$2015 \leq \varepsilon \leq 2018, \text{ for future estimations} \tag{26}$$

If ε < 2010 equation (24) produces invalid results; for values ε > 2018 it is highly likely that prediction attempts will have an associated error of ≥ 10% which is not an ideal option. For any ε satisfying restriction (25), substituting in equation (24) will lead to exactly the same results as already calculated and displayed in table 18.

Table 17 uses P1 to P5 for fitting traffic up to 2014. In order to make predictions about the monthly average traffic for period 2015 to 2018, it is obvious that the additional P_i's will be P6 to P9 respectively. Then, as these values progress at –0.002 for each P, P6 will be at 1.014, P7 at 1.012 etc., and this is exactly how the exponent works when combing the suggested arithmetical operations, variables and fixed numbers. However, those who make use of formula (24) do not need to know what the procedure is behind but only replace the necessary parameters. And this is the main reason why a so simple and robust scientific formula has been chosen: To be used by everyone who possesses elementary mathematical or computing skills. For example, to project traffic per month for 2015 we substitute the historical traffic of 2014 and the year accordingly, thus equation (24) becomes:

$$\mathrm{AMS.IXP}(2015) = \mathrm{AMS.IXP}(2014)^{\frac{24-2(2015-2010)}{1000}+1} \tag{27}$$

At this stage, the following question arises: For AMS.IXP(2014) in the right-hand side of (27), which figure from table 18 must be substituted, is it the fitted (1158353) or the actual (1190236)? The answer lies to the fact that investigation is based on the fitting procedure on the one hand, but both fitted and real values are almost the same on the other hand. The reason for proposing (27) – and as a matter of fact any prediction equation in this work – is because it is solely based on historical fitted traffic but, as expected, the latter is nearly equal to the actual because of the very small fitting error. Therefore, using either value makes almost no difference. However, it is recommended that actual figures should be preferred in case they exist. For instance, when forecasting traffic for 2015, we need historical traffic for 2014, for which the actual value does exist in table 18 and is therefore preferred. But if, for example, we need projections for year 2017, there is no actual figure for 2016 available at the moment thus the only option is to use the proposed fitted traffic for 2016 (which is to be included in a separate table in the next section). Back to (27), we solve the equation by substituting AMS.IXP(2014) with the actual figure (1190236) as proposed and we compute the estimated traffic for the Amsterdam Internet exchange point for year 2015:

$$AMS.IXP(2015) = 1190236^{\frac{24-2(2015-2010)}{1000}+1} \Rightarrow$$

$$AMS.IXP(2015) = 1447745\ TB/month \tag{28}$$

This figure is the average monthly traffic; to estimate the aggregated traffic for the whole year 2015, a multiplication by 12 is required. The monthly traffic has been selected instead of the yearly figures in order to be consistent with the global IP volumes of table 1. The latter is investigated to detect patterns and provide forecasts, which is an additional project and is presented in chapter 5.

4.5 Future Projections: Analysis and Discussion of Results

The macroscopic estimates for the next four years (2015-2018) for the Amsterdam IXP traffic are presented in this section. For this reason, equation (24) will be used to form the anticipated figures of the future based on the fitting properties of the exponent as year ε increases. The power value of (24) is assigned to P6 to P9 to predict traffic for 2015 to 2018 respectively and results must show the nature of the future tendency when compared to the past. As discussed, all "near" long term projections are expected to follow the trend of the historical record provided all assumptions meet the four criteria as described. All data from 2010 to 2018 are, more or less, expected to display a smooth progression from the past towards the future. The next table 19 presents the monthly average volumes as well as their respective annual growth. The latter is calculated as the ratio of the traffic for a given year to that of previous year.

Year ε	Data type	AMS.IXP(ε) (TB/month)	Annual Growth Rate
2015	Forecast	1447745	1.216
2016	Forecast	1716407	1.186
2017	Forecast	1981374	1.154
2018	Forecast	2225062	1.123
Estimated Average AGR			**1.17**

Table 19: Amsterdam IXP traffic projections

Figure 26 demonstrates the excellent ability of the proposed formula to maintain the same trend between the historical (actual) and projected data, especially for the regression line that represents traffic from 2012 to 2018. Similarly in figure 27, we observe a stable decline in all annual growth rates which, apart from a slight deviation in 2013, follow as well a fixed trend. In both graphs, the future strongly depends on the past characteristics and, based on this, it is almost certain it can be successfully predicted.

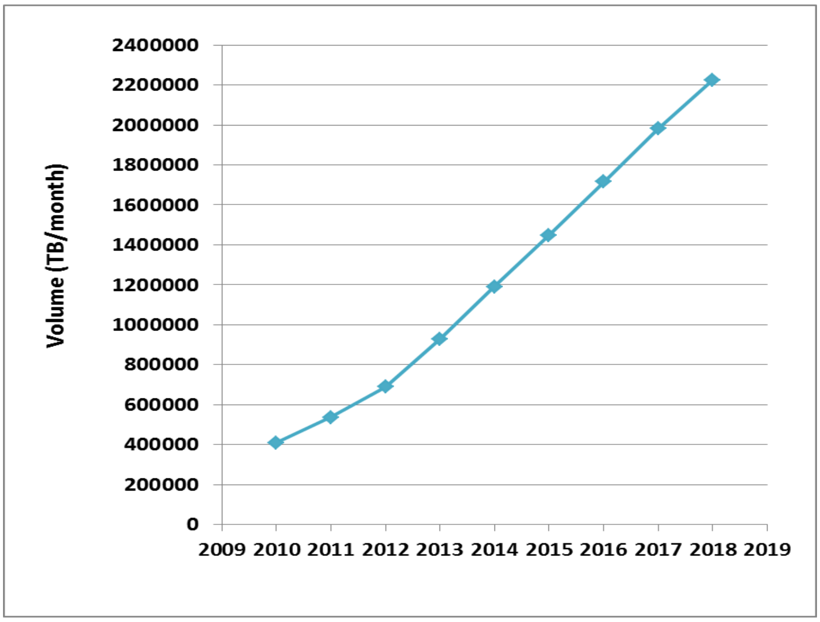


Figure 26: Trend progression: actual (2010-2014) and estimated (2015-2018) traffic data

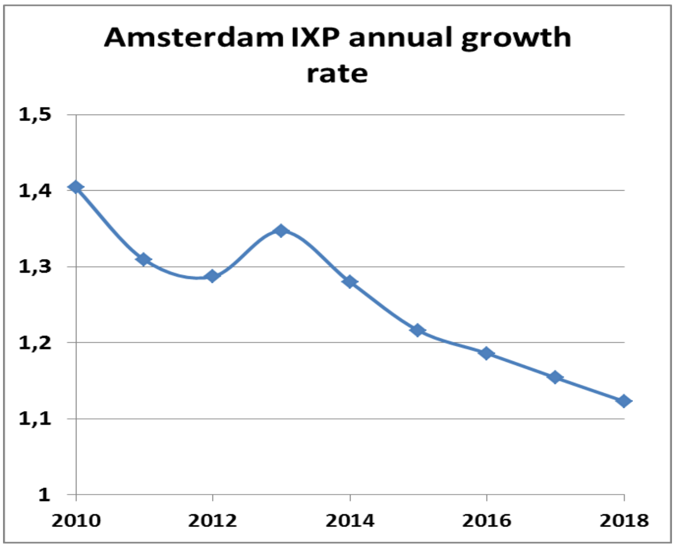


Figure 27: Historical (2010-2014) and estimated (2015-2018) AGR

Furthermore, the outcomes as displayed in the table appear reasonable in the sense that traffic will be still increasing in the future and the annual growth rate will continue to have declining characteristics year over year. Although there do not seem to exist similar studies to project traffic for the Amsterdam IXP, forecasts for the global aggregates are in the same line: global IP traffic still increases and the respective AGRs are declining. For the IXP traffic, if annual growth rates of the past (table 15) are compared with the estimated from table 19, there is a nearly steady decay expected until 2018. However, those annual growth figures here seem to be unusually low given the information presented in chapters 1 and 2. Furthermore, it can be expected that the global IP growth rate will end up between 1.30 and 1.35 for the global IP traffic, as demonstrated later in chapter 5 which immediately follows. Undoubtedly, the worldwide total figures are indeed different from those that come from local-scale sources such as IXPs, but on the other hand traffic that crosses large geographical areas can be expected to behave similarly with the total global traffic. The latter when compared to the Amsterdam Internet exchange displays higher traffic activity, increased at around two orders of magnitude. If traffic statistics of the future are found to be very close to the numbers as shown in table 19, then some other sources of traffic at some other location(s) in the world are likely to have much higher growth rates to balance the average total global volume. Those regions may involve certain countries of which their traffic growth and bandwidth offered are increasing faster than others and may involve higher socio-economic growth rates. Reports from Cisco in June 2008 for the total IP traffic, predicted a CAGR of 61% for Latin America for the six year period 2007 to

2012, while for the same timeframe the corresponding CAGR for Western Europe was estimated to reach 52% [Cis2008], [Cis2008b]. In addition, the same company in a more recent report in June 2014 projected a CAGR in IP traffic for Middle East and Africa at 38% in 2013-2018 which is the highest rate, as opposed to the 18% for West Europe which is the lowest [Cis2014a, p.6]. Similar CAGR figures for other types of regional traffic appear in numerous compiled tables in [Cis2014a], where Middle East and Africa have the highest CAGR while West Europe has one of the lowest. An example can be seen in the following table.

CDN Traffic, 2013–2018							
	2013	2014	2015	2016	2017	2018	CAGR 2013–2018
By Geography (PB per Month)							
North America	5,609	7,538	10,187	13,627	18,018	23,064	33%
Asia Pacific	3,310	4,446	6,171	8,474	11,631	15,909	37%
Western Europe	3,137	4,021	5,195	6,790	8,907	11,724	30%
Central and Eastern Europe	522	704	1,059	1,542	2,233	3,184	44%
Latin America	483	613	842	1,127	1,488	1,939	32%
Middle East and Africa	114	165	250	373	535	722	45%
Total (PB per Month)							
CDN Internet traffic	13,175	17,488	23,703	31,933	42,813	56,542	34%

Table 20: Estimated Internet traffic in Content Delivery Networks [Cis2014a, p.9]

Even though the top 3 continents of table 20 are responsible for approximately 90% of the total volume, their six year growth is lower than that of other regions. In general, there may be a number of important factors affecting traffic growth rates and may include the following two:

(i) Recent economic recession in North America and/or financial crisis in Europe.

(ii) Possible traffic saturation in populated countries in Europe and/or North America.

Although these topics are not a subject of the thesis, it might be worth to be taken into consideration for research, as their investigation may have implications on the technical part. Internet traffic is generated mostly by users which, in turn, may have strong connections with economic, social and other situations that could have adverse effects in Internet usage. In the meantime, nevertheless, certain evidence of traffic decline as discussed in the introductory and literature chapters is already a fact. Eventually, projections of traffic for the Amsterdam Internet exchange as pictured in table 19 may be proved to be accurate. In anticipation to the actual traffic, complete 2015 aggregate figures should be available early 2016.

4.6 Evaluation

Usually, there are two methods to determine the quality of a model:

(i) Going back in time several years to test the validity of the "future" values (up to the last present historical volume).

(ii) Evaluate predictions based on the actual traffic figures when they become available.

The former has been already accomplished at the fitting stage as demonstrated and is considered successful. Judging a model's real quality, however, must be supported with convincing evidence for the purpose it has been designed for. The fitting process is the reference technique that will lead to accurate forecasts, but the real purpose of the suggested equation is its actual predictability. Therefore, real traffic figures will be compared to the estimated for the proposed timeframe 2015-2018. As of January 2016, all traffic at the Amsterdam Internet exchange point for all months for year 2015 has been released; all figures are available at the Amsterdam IXP statistics website [Ams2015]. Note that studies of this chapter have begun in September 2015 but this section is composed just after the end of 2015 to perform the evaluation stage when the new figures had become available. The same process is applied to all evaluation sections in all chapters (where applicable) with results and discussion as appropriate.

For the IXP historical statistics at Amsterdam, after adding up monthly volumes for incoming and outgoing traffic the aggregate number is divided by 12 to form the average final figure. The following table summarizes the necessary information; however it does so only for the available traffic for 2015.

Year ε	**Projected AMS.IXP(ε)** (TB/month)	**Actual AMS.IXP(ε)** (TB/month)	**Prediction error (%)**
2015	1447745	1509995	4.13
2016	1716407	Not available	-
2017	1981374	Not available	-
2018	2225062	Not available	-
Average prediction error (so far)			**4.13**

Table 21: Evaluation results for the Amsterdam IXP forecasts

Using equation (5) from section 2.9 and substituting values accordingly for year 2015, the associated forecasting error is calculated at only 4.13% thus the ideal target of producing a predictability rate below 5% has been achieved for the Amsterdam IXP. The rest of the pending actual data will be made available on a yearly basis and by the end of the suggested timeframe the model will be evaluated in total. In any case, the average figure must be lower than 10% to be regarded as successful.

CHAPTER 5

Forecasting Volumes on a Global Scale: the Total IP Traffic

"What we know is a drop,
what we do not know is an ocean"

- Sir Isaac Newton

The totality of the generated traffic across the Internet can be predicted based on sufficient historical measurements. This chapter presents the proposed method and formula to project the aggregate Internet Protocol (IP) traffic across the entire Internet. Evaluations on predictions for the suggested future timeframe have shown excellent results with a very low forecasting error rate.

5.1 Global Facts

Worldwide Internet traffic encompasses all types of activity and each type is responsible for small or large parts of the total flow. Historical traffic evidences fixed Internet to be the dominating part of the overall IP figures but, at the same time, mobile technologies seem to grow at a faster pace and tend to absorb a larger share in the last several years according to Cisco. From another point of view, Internet users respond in a different way towards market challenges, especially when technological advances bring forward new applications and hardware, such as i-phones, smart TVs and wireless wearable equipment. Unless it is something very popular and extraordinary that breaks into the market, most of the traffic those devices generate at their rapid growth stages usually accounts for small percentages when compared to the whole transmitted activity across the Internet. Nevertheless, certain technologies can boost global IP traffic to increase significantly some time, for instance streaming media webpages. The behavior of Internet users along with the increased demand for bandwidth may be important factors to be taken into account when trying to predict future traffic. Some of those assumptions may be part of the methodology used in [Cis2012, Cis2008, Cis2008b, Cis2013b, Cis2014a] to predict global volumes, along with further technical assumptions and other information from a variety of companies. In this thesis, however, and specifically in this chapter none of those assumptions or any socio-economic facts have been taken into consideration. The proposed prediction methodology has been exclusively derived from a large number of experiments and from numerical properties of historical statistics.

There are available measurements from all global networking systems which can indicate forthcoming traffic; the IP traces in table 22 will be used for this purpose. In these studies, selecting the appropriate model is based on the arithmetical properties of global traces that have been captured from the past. Therefore, appropriate characterization of the figures of the series of table 22 must be achieved in strict chronological order. The proposed analytical investigation is to be applied to the IP volumes, as those figures have been collected from all global activity and are preferred to smaller samples such as the fixed or the managed IP traffic. Studies are specifically focused on the progression properties of numbers for the 2005-2011 timeframe and on hidden relations to be revealed in consecutive values to produce subsequent numbers.

Global Internet Protocol (IP) Traffic (PB/month)	
Year ε	**Total measured volume**
2005	2,426
2006	3,992
2007	6,430
2008	9,927
2009	14,414
2010	20,197
2011	27,483

Table 22: IP historical figures for the entire Internet [Cis2013]

There are certain patterns that have been found in the historical values, for which a relation can be produced to model history activity and produce accurate forecasts. If that trend is the case, it is highly likely to provide us with precise projections at an average prediction error rate ideally lower than 5% for 2012 to 2015 inclusive, but certainly less than 10%.

5.2 Hidden Properties in Historical Sizes

IP volumes in table 22 incorporate certain progression attributes; the main hypothesis here is that a value of a given year in PB/month has an influence to that of next year, and vice versa, for 2006-2011. Apparently, this means there is an explicit relation between all IP figures in each consecutive pair that can describe their connection and in particular between 2006 and 2005, 2007 and 2006 and, in general, between any years ε and ε–1. All sets of relations have been observed to have common parameters and the hidden numbers of the parameters have a relation for each pair. In turn, the common parameter which exists in each pair has a different value but there is a hidden relation that connects it in all pairs as values progress in time. To justify the aforementioned assumption, the following important observations are a fact for all global IP numbers:

(i) Each of those numbers is a multiple of 1.5 (±0.2 maximum deviation) when compared with the previous number as the associated period progresses at +1 for the observed values for years 2006 until 2011.

(ii) Numbers seem to be increasing at a steady order across the years with no significant irregularities or spikes seen in their data, i.e. they exhibit smooth progression characteristics.

In other words, (i) is another evidence of the declining nature of traffic growth and (ii) implies it is almost granted there is a form of equation that connects all involved numbers. Again, as in all chapters, no software has been used or does exist until today to reveal the proposed methods or equations, but it is only based on intelligence and extensive experimentations.

Proceeding to the core part of the project, an explicit relation must be formed to characterize the set of inputs (years ε–1) and the permissible set of outputs (years ε). All involved variables and constants are straight-forward and the assumption is to include year ε which is to be substituted at the calculation processes. Forecasts are expressed in

PB per month and depend on historical traffic which again highlights a strong relation between the future and the past. As demonstrated in earlier chapters, an exponential-like equation has been proved efficient and the same generic format is used here as well. Apart from this reason, an exponential form is suitable for potential updates in case future figures indicate so. Although traffic growth is probably expected to decline for the global traffic too, the opposite should not be totally excluded at some time in the future thus an exponential representation of the following form (equation 29) is always flexible to updates:

$$G.IP(\varepsilon) = [G.IP(\varepsilon - 1)]^{P} \tag{29}$$

Notation G.IP(ε) is the worldwide (global, G) Internet Protocol (IP) total traffic which we want to predict for year ε and G.IP(ε–1) refers to the historical figure that has been measured in year ε-1. The exponent P is to be detected separately for all historical values as described in the methodology procedure. According to (29), to forecast IP traffic in year 2012, for instance, we substitute available traffic for 2011 with 27483 PB/month from table 22:

$$G.IP(2012) = [G.IP(2011)]^{P} \Rightarrow$$

$$G.IP(2012) = 27483^{P} \tag{30}$$

However by the time of these studies, traffic for 2012 was not available thus P is not known. Relation (30) has two unknown variables, therefore patterns cannot be detected since only known numbers will be taken into account. Consecutive traffic figures are now considered to reveal exponent P, therefore values of all P_i for each pair will be put into the proposed experimentation set. Figures are substituted using (29) accordingly and all possible pairs are expressed as:

$$G.IP(2006) = [G.IP(2005)]^{P1} \Rightarrow 3992 = 2426^{P1} \tag{31}$$

$$G.IP(2007) = [G.IP(2006)]^{P2} \Rightarrow 6430 = 3992^{P2} \quad (32)$$

$$G.IP(2008) = [G.IP(2007)]^{P3} \Rightarrow 9927 = 6430^{P3} \quad (33)$$

$$G.IP(2009) = [G.IP(2008)]^{P4} \Rightarrow 14414 = 9927^{P4} \quad (34)$$

$$G.IP(2010) = [G.IP(2009)]^{P5} \Rightarrow 20197 = 14414^{P5} \quad (35)$$

$$G.IP(2011) = [G.IP(2010)]^{P6} \Rightarrow 27483 = 20197^{P6} \quad (36)$$

Common variable P has been separately assigned to P1, P2, P3, P4, P5 and P6 for the timeframe 2006 to 2011 to relate period 2005 to 2010 respectively. All P_i's (index i = 1 to 6) are the key to detect patterns, if any, between volumes for years ε and ε–1 and some common parameters – constants and/or variables – will appear in the exponent later to formulate the final equation. Again, using the known logarithm property relations from chapter 4, we now solve equation set (31) to (36) to calculate P_i rounded to the closest sixth decimal digit and the table that follows indicates respective values.

Relation	**Value of P_i**
$3992 = 2426^{P1}$	1.063902
$6430 = 3992^{P2}$	1.057487
$9927 = 6430^{P3}$	1.049526
$14414 = 9927^{P4}$	1.040524
$20197 = 14414^{P5}$	1.035227
$27483 = 20197^{P6}$	1.031073

Table 23: Respective P for equations (31) to (36)

5.3 Fitting Historical Trends

The produced P values have decreasing characteristics between the range 1.063902 and 1.031073 but no fixed variable seems to be matching a fixed subtraction to form the next number as P reduces down to 1.031073. As opposed to the Amsterdam IXP traffic numerical properties, the progression from 2006 to 2011 for which the global IP figures exhibit over the historical trend is more complicated. Initially, the following relations are observed:

$P1 - \Omega 1 = P2$

$P2 - \Omega 2 = P3$

$P3 - \Omega 3 = P4$

$P4 - \Omega 4 = P5$

$P5 - \Omega 5 = P6 \Rightarrow$

$$P_i - \Omega_i = P_{i+1} \qquad i \in [1, 6] \qquad (37)$$

Variable Ω_i does not seem to accommodate a "convenient" property or a relation which can be expressed with a fixed number. When observing P1, P2 and P3 it looks like their difference can be expressed with:

$$\Omega = 0.007 \cdot C \qquad C = 1, 2 \qquad (38)$$

However, pattern in (38) is not consistent for subsequent values P4, P5, P6 and, furthermore, for the latter three variables their difference shrinks down when approaching the final value of P6. This variation along with the previous brings more difficulty to the pattern detection process and at this stage extensive trials with specific ranges of Ω are put into the experiments to reveal the combination of P_i's and Ω_i's to produce the lowest deviation, which is to define the fitting error.

In any case, the associated error must be kept at a reasonably low figure and at the same time the range of the exponent must be continuously re-calculated, so that it can clearly formulate a pattern. After large-scale numerical experiments, the exponent's upper limit and lower limits have been computed to combine precise values with very low errors. Relations (31) to (36) by using the fitting values have been found to exhibit minor deviations when compared to the actual which in turn suggests a low fitting error, less than the average that was found for the Amsterdam IXP. The new particular range has excellent fitting characteristics and all selected values for P produce almost the same numbers with the available historical data in table 22. Results are pictured in table 24 and calculations of fitted G.IP(ε) figures are rounded to the closest integer (PB/month).

Proposed P_i	**$[G.IP(\varepsilon\text{-}1)]^{P_i}$**	**Fitted G.IP(ε)**	**Actual G.IP(ε) (Historical)**	**Fitting Error (%)**
1.0645	$2426^{1.0645}$	4011	3992	0.47
1.0560	$3992^{1.0560}$	6351	6430	1.23
1.0485	$6430^{1.0485}$	9838	9927	0.90
1.0420	$9927^{1.0420}$	14611	14414	1.37
1.0365	$14414^{1.0365}$	20445	20197	1.23
1.0320	$20197^{1.0320}$	27737	27483	0.92
Average Fitting Error				**1.02**

Table 24: Fitting results of the proposed method

The mean six-year fitting error calculated at as low as 1.02% is regarded as exceptionally low. It is obvious that numerical experimentations have come up with excellent alternative data as shown in the fitted G.IP(ε) data column in table 24. Moreover, the progression characteristics of the proposed fitting data demonstrate an almost identical regression curve when they are compared with the actual traffic (figure 28) suggesting that future trends are highly likely to be in the exact same line with this pattern. Although fitting data points are discrete in time, their smooth progression represents the connection of traffic volumes year over year. Since the sample comes from the totality of the history of Internet activity, it is strongly suggested that the specific trend will be almost the same for the next few years.

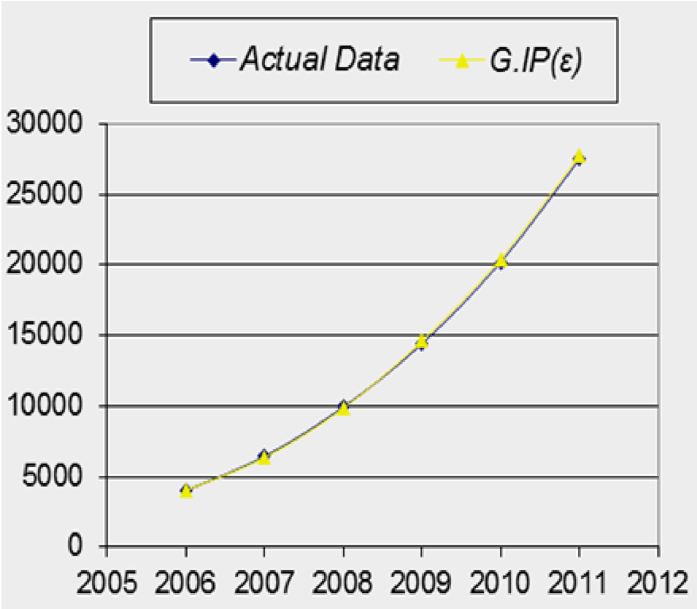


Figure 28: Historical global IP volumes compared to the fitted

5.4 Formulating the Appropriate Equation

The pattern detection stage depends on finding an accurate progression property for all numbers as shown in decreasing order in the first column of table 24. Variables P1 to P6 have been observed to decay gradually, not at a stable rate (e.g. at –0.002 as detected in previous chapter) but with some level of peculiarity. By bookkeeping all extracted relations of P1 to P6 using some complex operations, numerical experiments have successfully indicated a hidden relation which is explicitly expressed with equations (39) to (44):

$$1.0645 = 1 + 0.0645 \tag{39}$$

$$1.0560 = 1 + 0.0645 - 0.0085 \tag{40}$$

$$1.0485 = 1 + 0.0645 - (0.0085 + 0.0075) \tag{41}$$

$$1.0420 = 1 + 0.0645 - (0.0085 + 0.0075 + 0.0065) \tag{42}$$

$$1.0365 = 1 + 0.0645 - (0.0085 + 0.0075 + 0.0065 + 0.0055) \tag{43}$$

$$1.0320 = 1 + 0.0645 - (0.0085 + 0.0075 + 0.0065 + 0.0055 + 0.0045) \tag{44}$$

All relations add an extra number each time which appears inside the brackets and this happens each time as P decreases. In addition, they have several repeating constants and some common variables which decrease by 0.0010. Again, by carefully observing (39) to (44), the pattern has been verified with certain combinations of arithmetical operations using numerical programming and the final relation must be now confirmed. Proceeding to the main formula, the aforementioned properties are being considered and more variables and parameters are added as necessary. The final format of the proposed equation comes as a result of bookkeeping all extracted relations so far, consistent observations in numerical experiments and a standard level of intellectual abilities. Equation (45) is the hereby proposed model including year ε for historical fittings and future estimations.

$$G.IP(\varepsilon) = G.IP(\varepsilon - 1)^{\frac{645-[90-5(\varepsilon-2006)](\varepsilon-2006)}{10000}+1} \tag{45}$$

$$2006 \leq \ \varepsilon \leq \ 2011, \text{ for fitting purposes} \tag{46}$$

$$2012 \leq \ \varepsilon \leq \ 2015, \text{ for predictions} \tag{47}$$

Obviously at some time after the end of year 2015 when all measurements will become available, relation (45) can be used to fit data until 2015 in order to forecast figures for the next few years, e.g. for 2016-2018. Restriction (47) is the recommended limited prediction timeframe to avoid huge forecasting errors and uncertainties. This four-year horizon is probably an optimum selection to keep the associated error below 10% and to maintain the traffic trends of the past. The fourth year is to test if forecasting error rates are to suggest a 3-year timeframe instead. Strategical planning and financial investing would perhaps be more efficient if the selected period would look quite several years ahead, e.g. even up to 10, but in this way misleading information caused by high prediction errors in the long term could have negative impacts to companies and ISPs. In any case, it is advised that (45) be revised shortly after 2015.

5.5 Future Projections

Although the selected model has excellent results with historical fitting, speculations for the near or distant future shall be always susceptible to errors – the longer the forecasting horizon the higher the risk of coming up with inaccurate figures. An explicit example is the Cisco case where the respective Historical Average Prediction Error (HAPrE) has been calculated at more than 10% as analyzed in the literature part. For the present studies, introducing a novel forecasting model such as formula (45) does not necessarily imply 100% precise results or even close to that. Even though the mean fitting error has been computed at only 1.02%, there is no guarantee that future traffic will behave similarly. However, the suggested relation is expected to provide high prediction accuracy if there is stability in Internet user trends and market consuming power. Considering any potential adverse implications of the distant future, the proposed forecasts are targeted to period 2012 to 2015. The following table presents the expected average monthly figures in PB per month of the total global IP traffic calculated with the proposed equation, along with a 2016-2017 "guesstimate". The latter is a term used in [Per2003] for future outlooks but it should not be regarded as suitable for this work, hence the wide range given instead of precise figures.

Year ε	**Data type**	**G.IP(ε)**	**AGR**
2012	Forecast	37127	1.35
2013	Forecast	48809	1.31
2014	Forecast	63587	1.30
2015	Forecast	82918	1.30
Average estimated AGR 2012-2015			**1.315**
2016	Guesstimate	95000 - 115000	-
2017	Guesstimate	124000 - 141000	-

Table 25: Projections of traffic volumes with respective growth rates

A decline in the AGR as shown in the table is reasonable and, furthermore, the average estimated IP growth rate at 1.315 is quite realistic considering the recent and not so recent decay characteristics of historical traffic. The same trend is estimated to progress until at least for 2014 and maybe up to 2017. However, there are a few issues that seem to be unclear, considering the distant macroscopic traffic behavior:

(i) Whether the decrease in AGRs will continue or not in the far future, i.e. from 2016 and onwards.

(ii) At which point we expect saturation to begin (if any), i.e. for which year(s) would the corresponding growth rate be calculated at nearly 1 or less.

Those issues derive mainly from the uncertainty peculiarities of the very long run and, in general, from what we can expect in several years ahead. As a result, there are more relevant issues that can be brought forward such as the technical implications (e.g. hardware configurations, bandwidth demand, energy supply) as well as associated financial risks that investors would first want to think of. However, the technology advances that are about to come, the significant rise in mobile Internet traffic and the domination of 4G/5G smart and wearable devices indicate that traffic saturation is still far from us. Specifically, it is not expected that global traffic will decline as a whole but the opposite is more likely to happen: it should continue to grow beyond 2015 as demonstrated in related studies by [Kor2013], [Cis2008], [Cis2008b], [Cis2012], [Cis2013b], [Cis2014a].

The next two figures show graphical representations of the results of table 25. In figure 29 it is clear that estimates using the proposed formula are absolutely consistent with historical progression while graph 30 shows a reasonable further decline in the annual traffic growth rates.

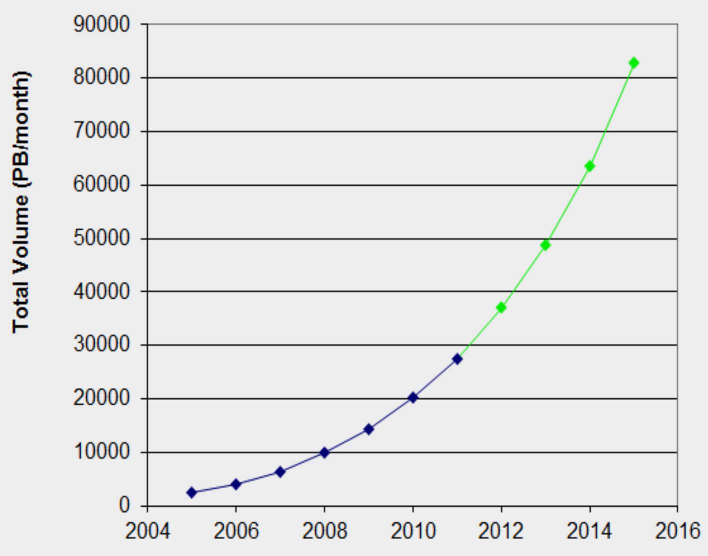


Figure 29: Historical (blue) and projected (green) total global IP traffic

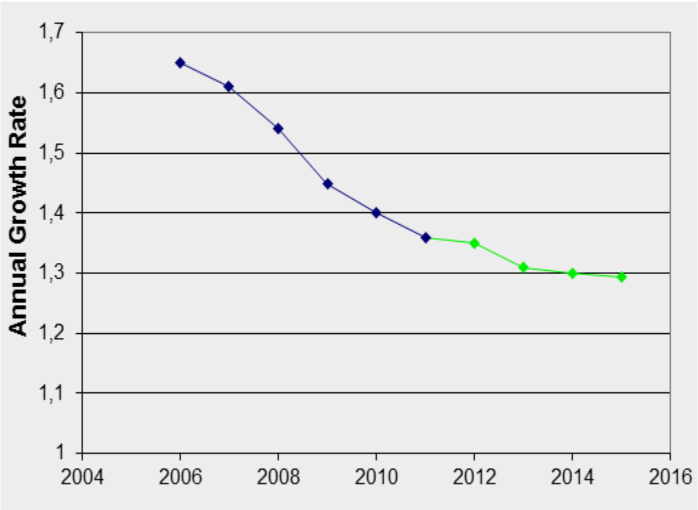


Figure 30: Historical (blue) and estimated (green) AGRs of IP volumes

5.6 Further Analysis

The hereby suggested function derives from repeated experiments which have set the format of the equation as presented. The parameters have been selected after a few millions of comprehensive calculations to determine a low error and minimize the effort to form a reasonable complex relation. As described in Leonard Euler's work "Mathematics by experiment" in book [Ngu2011], patterns can be detected using "The Scientific Method" or "The Mathematical Method" by keeping a good record of the data to allow relations to be easily observed. Part of those ideas have been as well applied for this thesis but it is reasonable to say that perhaps there is another similar relation which might produce better results – fitted and forecasts – and which has not come to my attention yet. The extremely large number of computations may have missed optimum choices to assign specific numbers to variables and constants, but this is reasonable too. When actual data prove or disprove the proposed model, any further updates must realize even slight variations of the involved parameters can affect the exponent and final results seriously. A general representation of possible updates in the future may be given with the following expression:

$$G.IP(\varepsilon) = [G.IP(\varepsilon\text{-}1)]^{\Delta P/\Delta T(\varepsilon-1)} \tag{48}$$

ΔP is to indicate a certain degree of variation when new measurements can be compared with the historical traffic by that time. $\Delta T(\varepsilon-1)$ refers to the changing trend that each of the historical years exhibit by the time when new studies, if any, are to revise the proposed model. Even in the ideal situation where forecasts will be proved to be absolutely successful, an extensive revision of the formula using updated facts can give even more precise figures. A possible change in Internet users' behaviour, especially for the high-impact global traffic sources, would mean some level of improvement. Some degree of change in the trend over the years may add or remove existing variables and/or constants in (45). Alternatively, the nature of this change may prioritize different operations to be considered for the new formula or simply altering specific numbers in the exponent. At this point it is reminded that any updates on new data must take into consideration all four criteria exactly as described in the third chapter.

The static characteristics of the proposed studies exclude forecasts that have severe fluctuations. However, the presence of many numbers in the main equation allows certain changes to take effect, even though there is some complexity in the exponent. Apart from the year, most of the selected constants give more detail to results and may set the slope of the graphical representation at varying levels. Minor modifications of such numbers have been put into experimentations and it has been observed that those changes could be sufficient. According to the past trend of 2005 to 2011, an appropriate extrapolation of a possible future trend within some limited range can be represented by updating the decay rate using constant 90 in the formula. Numerical results have indicated a good response, in the meaning that extrapolated figures do not significantly deviate from the initial calculations. Thus, equation (45) could be of the following general format:

$$G.IP(\varepsilon) = G.IP(\varepsilon - 1)^{\frac{645 - [\Delta F - 5(\varepsilon - 2006)](\varepsilon - 2006)}{10000} + 1} \tag{49}$$

More specific, the constant term 90 has been replaced with variable ΔF and has been selected over other numbers from the exponent mainly because it does not produce undesired results. ΔF has been assigned a suitable range and is between 82.5 to 92.5, which has slightly changed the slope of the original curve – the upper and lower limit – as shown in the following figure:

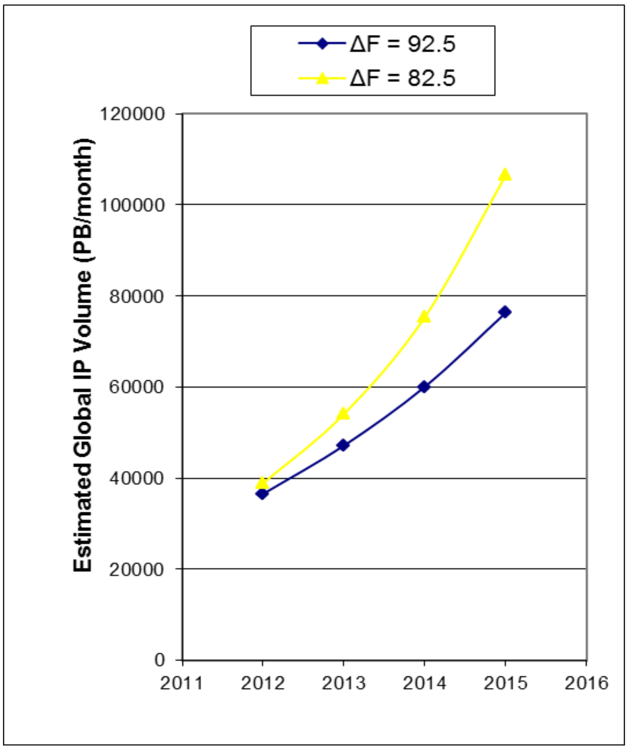


Figure 31: Extrapolated estimates for 2012-2015

The expansion of the range falls within ±10% of the initial graph included in an earlier section and is an alternative representation and at the same time it is a potential update of the original formula. However, the exact value of ΔF is to be determined in the future, if applicable, and according to the new traffic figures.

5.7 Evaluation

The ultimate target of coming up with a prediction error of no more than 10% (and ideally less than 5%) when some new measurements would be known, is now a fact. Global figures for 2012, 2013 and 2014 have been made available to the public from Cisco Systems. The following table highlights successful predictions by the time respective studies were conducted. Again, relation (5) from section 2.9 is employed to calculate yearly forecast error rates.

Year ε	**Projected G.IP(ε)** (average PB/month)	**Actual G.IP(ε)** (average PB/month)	**Prediction error (%)**
2012	37127	38300	3.06
2013	48809	47400	2.97
2014	63587	59800	6.33
2015	82918	Not available	-
Average prediction error (so far)			**4.12**

Table 26: Demonstration of the goodness of the proposed model

The average error rate at 4.12% is of excellent accuracy so far and seems to be the most accurate result in all relevant studies for predictions focused on the long term. In anticipation to 2015 global IP traffic, the average rate will most likely stay below 5%, however this is not guaranteed mainly because the proposed prediction timeframe has been set to only three years, i.e. 2012 to 2014 inclusive. The additional fourth year of 2015 has been included only to test the predictability of the model beyond the proposed period which, in general, is not advised. And as already demonstrated, forecasts targeted to the very long run are susceptible to excessive errors and should be avoided.

CHAPTER 6

Forecasting Global IP Traffic: an Alternative Method

"No great mind has ever existed
without a touch of madness"

- Aristotle

Another method to project IP traffic for the whole Internet infrastructure is presented in this part. The main assumption is to include additional historical data from two or more consecutive years to make predictions. This approach has been proved successful as well, albeit with a higher associated error when compared to that of previous chapter.

6.1 Increasing the Dependence of the Past

One of the main findings of the previous chapter was the strong influence of historical measurements to make accurate forecasts. Generally for predictions, there are additional methods to produce accurate results which are not as popular as NN or ARIMA models, but are efficient as well. A good example is the study in [Tia2015] where a hybrid Gauss process is proposed to predict network traffic. The authors' novel idea improves the forecast accuracy, even if the method seems to be quite different from traditional time series modelling. Broadly speaking, we may witness certain studies in the near or far future that would have never been proposed several years ago mainly because they are much different from existing ones. In this chapter another relation is brought forward to project global IP traffic which is based on extracting patterns through available historical figures, but this time from all years for which we have got pertinent data. The central hypothesis of this idea suggests that the total traffic for any year ε can be estimated using either:

(i) Two consecutive years' figures ε–1 and ε–2 instead of one.

(ii) Volumes of any number of historical years in any order, as appropriate.

This proposal would emphasize the dependency of the history traffic towards the future trends, again for the next three to four years maximum. Approach (i) seems to be more feasible as advised in the next section.

6.2 Leonard Euler: "The Sum of Divisors"

Some specific part of the idea used herewith has been inspired from Nguyen (2011) and is the exclusive work from one of the greatest minds and Mathematicians of all time, Leonard Euler [Ngu2011]. "The sum of divisors and the pentagonal number theorem", as presented by Leonard Euler, is included in chapter one in [Ngu2011] in which it is clearly emphasized that Euler was an excellent bookkeeper of relations. Euler's technique is looking for patterns that can be recursively defined in certain consecutive numbers as shown in the next table.

n	σ(n)	σ(n–1)	σ(n–2)
1	1	--	--
2	3	1	--
3	4	3	1
4	7	4	3
5	6	7	4
6	12	6	7
7	8	12	6
8	15	8	12
9	13	15	8
10	18	13	15

Table 27: Elements σ(n), n = 1..10 [Ngu2011, p.8]

To begin with, numbers σ(n), σ(n–1), σ(n–2) have been put into order according to ascending degree of n as demonstrated and then the following relations can be easily observed [Ngu2011, p.8]:

$$\sigma(3) = 4 = 3 + 1 = \sigma(2) + \sigma(1) \tag{50}$$

$$\sigma(4) = 7 = 4 + 3 = \sigma(3) + \sigma(2) \tag{51}$$

Ideally, this would continue for all subsequent elements of n for table 27 with a fixed equation of the following expression:

$$\sigma(n) = \sigma(n-1) + \sigma(n-2) \tag{52}$$

Unfortunately this pattern fails to continue for n = 5 or more and, thereafter, Euler applies different mathematical methods which are not suitable to this work and are not analyzed. For this thesis, however if a parameter ρ could be added/subtracted accordingly so that the pattern holds for larger n's, then some equation of the following format could be suitable for the scope of this chapter:

$$\sigma(n) = \sigma(n-1) + \sigma(n-2) \pm \rho \tag{53}$$

Notation ρ can be a constant, variable or a whole expression. Its value is critical and experiments will be carried out through the next sections to detect the exact format of ρ. It is clear that numbers in table 27 do not display a fixed ascending pattern as n increases, which is necessary for these studies and is a restriction as defined by the four criteria. Relation (53) can be amended accordingly to predict traffic for a certain year as a function of the two previous years by looking carefully at the numbers as they increase in time.

6.3 Relating Traffic Recursively

The idea based on Euler's method will be used to project the global IP figures. Therefore, the next table 28 has been formed to include the available historical IP figures in a sense that it will look like table 27 to allow any relations to be revealed. In addition, an extra column produces all applicable additions on σ(n–1) + σ(n–2) to be compared with σ(n) and to reveal a possible value for ρ.

Year ε	n	Global IP traffic (PB/month)				
		σ(n)	σ(n-1)	σ(n-2)	σ(n-1) + σ(n-2)	Parameter ±ρ = ?
2005	1	2426	-	-	N/A	
2006	2	3992	2426	-	N/A	
2007	3	6430	3992	2426	6418	
2008	4	9927	6430	3992	10422	
2009	5	14414	9927	6430	16357	
2010	6	20197	14414	9927	24341	
2011	7	27483	20197	14414	34611	

Table 28: The alternative method based on Euler

Substituting accordingly n with ε to be consistent with the main formula, relation (52) becomes:

$$G.IP(\varepsilon) = G.IP(\varepsilon-1) + G.IP(\varepsilon-2) \tag{54}$$

In combination with (53), equation (54) is now expressed as:

$$G.IP(\varepsilon) = G.IP(\varepsilon-1) + G.IP(\varepsilon-2) \pm \rho \tag{55}$$

The sum σ(n–1) + σ(n–2) in the table is observed to be close to σ(n) for 2007 to 2011 but some number must be subtracted and this is where parameter ρ is to form a complex expression. According to all sums for n = 3 to 7, ρ seems to have an increasing pattern as year ε increases too, which if subtracted gives a very good approximation to the final result. Firstly, the expression of ρ is of the following form:

$$\rho = \delta + A \tag{56}$$

Letter δ denotes a variable; parameter A includes a constant and an additional variable C (C∈N) that has been calculated to be equal to:

$A = 495 \cdot C \qquad C = 1, 2, 3, \ldots$ (57)

C will be related to each year ε as appropriate, since the former increases at a rate of some positive integer which is convenient for the calculation set and year proceeds always at +1. All previous three expressions (55), (56) and (57) can be combined into one single equation:

$$G.IP(\varepsilon) = G.IP(\varepsilon-1) + G.IP(\varepsilon-2) - (\delta + 495 \cdot C) \quad (58)$$

This relation is to indicate the associated fitting error at the respective stage. However, the pattern detection according to the proposed method is far more complicated than in other chapters, thus the equation must be first revealed.

6.4 Mathematical Representation

By substituting G.IP(ε), G.IP(ε–1), G.IP(ε–2) with historical volumes and starting from year 2008, we must now proceed to detect any unknown variables. Initially, the following simple relations can be obtained:

$$G.IP(2008) = G.IP(2007) + G.IP(2006) - (495) \quad (59)$$

$$G.IP(2009) = G.IP(2008) + G.IP(2007) - (1943) \quad (60)$$

$$G.IP(2010) = G.IP(2009) + G.IP(2008) - (4144) \quad (61)$$

$$G.IP(2011) = G.IP(2010) + G.IP(2009) - (7128) \quad (62)$$

When combining (59) to (62) with relation (58), we get the following set of relations:

$$G.IP(2008) = G.IP(2007) + G.IP(2006) - (0 + 495 \cdot 1) \quad (63)$$

$$G.IP(2009) = G.IP(2008) + G.IP(2007) - (458 + 495 \cdot 3) \tag{64}$$

$$G.IP(2010) = G.IP(2009) + G.IP(2008) - (184 + 495 \cdot 8) \tag{65}$$

$$G.IP(2011) = G.IP(2010) + G.IP(2009) - (198 + 495 \cdot 14) \tag{66}$$

From those series of calculations, variable C increases as the historical timeframe increases too and for this reason there is a pattern satisfying the condition. However, δ does not have a consistent rate at all and therefore revealing a pattern for the whole set of equations (63) to (66) seems to be getting complicated. Indeed, the peculiarity of parameter δ forces the other two numbers to participate in a mixture of linear and exponential combination of operations and, all together, it has been of particular difficulty to include year ε as well. Other than the millions of calculations involved, some tricks had to be included regarding how the aforementioned numbers assigned to δ could be overlooked or simply be broken into more operations. Eventually, the latter was preferred rather than excluding the complex properties that δ exhibits, as this could lead to excessive fitting and/or forecasting errors. Performing a further extensive set of related numerical experiments and by bookkeeping all relations into separate categories, the following equation has been formed after great effort:

$$G.IP(\varepsilon) = G.IP(\varepsilon-1) + G.IP(\varepsilon-2) - \left[(\varepsilon - 2008) \cdot \left(2^{0.65+[0.25\times(\varepsilon-2008)]}\right) \cdot 800 + 495\right] \tag{67}$$

Apart from the difficulty described, the model as presented in equation (67) is of limited functionality in the meaning that the fitting process starts in 2008 due to Euler's recursive feature which requires at least two numbers of the past. On the other hand, the prediction timeframe remains the same as with the main relation, thus restrictions are categorized according to the purpose:

$2008 \leq \varepsilon \leq 2011$, for fitting (68)

$2012 \leq \varepsilon \leq 2015$, for estimates (69)

However, the numerical results that the formula produces seem to be of particular interest because they have very low levels of dispersion when compared to historical figures and this particular feature has been discovered at the large-scale computation process. Undoubtedly, the final format is of high complexity but, in fact, it seems to fulfil the purpose which it has been designed for as evidenced in the sections which immediately follow.

6.5 Existing vs. Fitted Data

Despite the intricacy of the proposed mathematical model, related fitting outcomes have indicated excellent response over the actual data points. The first version of the global IP formula in chapter 5 is certainly less peculiar but has a slightly larger fitting error compared to the second version of this chapter. Specifically, equation (67) produces an average deviation error of at only 0.47% which is an almost perfect result. Table 29 includes all results at the fitting stage. We can observe calculations with very low error rates against the actual traffic.

Year ε	**Fitted G.IP(ε)**	**Actual G.IP(ε) (Historical)**	**Fitting error (%)**
2006	-	3992	N/A
2007	-	6430	N/A
2008	9927	9927	0
2009	14369	14414	0.3
2010	20295	20197	0.5
2011	27782	27483	1.09
Average fitting error			**0.47**

Table 29: Characterization and fitting results of the second proposed model

The same fitting advantages are as well illustrated in the next graph. We can observe a perfect match of the two representations – fitted and actual – for which the future trend is expected to extend at a similar progression rate (figure 32). Fitted results are also in line with the first proposed model. Some analysis between the main equation of chapter 5 and this model, show respective data points for common historical years 2008-2011 to be located very near each other. However, the criterion described in the methodology section which states there must be at least four years of historical activity, has been just met with the present equation. In previous chapters and for all that follow, there have been more than four years included for the historical timeframe which means there is a stronger basis for research. For the proposed equation, there is a good review supported by evidence to be presented in the evaluation section (6.8) when projections of the model are compared with the actual figures.

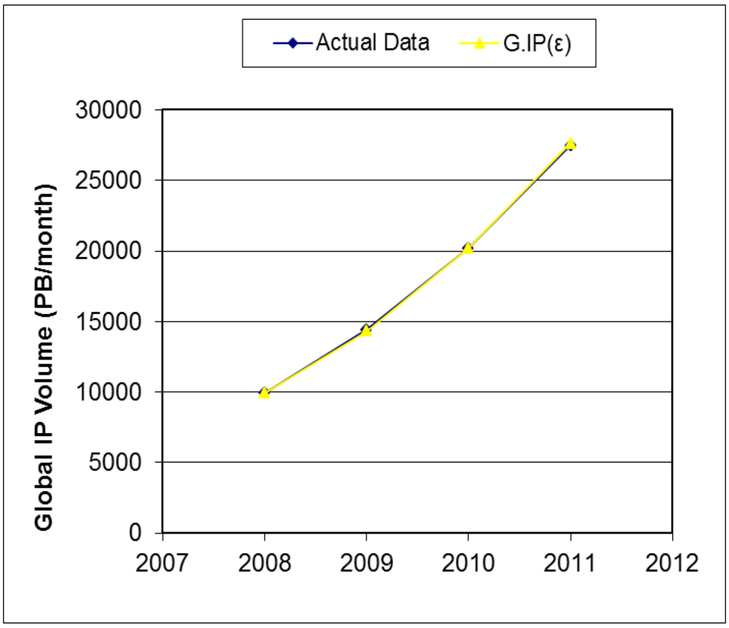


Figure 32: Identical graphs: fitted vs. real traffic

6.6 Future Estimates

By substituting variable ε with corresponding years 2012 to 2015 (equation (67), future projections for global IP traffic are eventually presented in table 30. In the four-year timeframe it is once more confirmed that annual growth is expected to decline down to around 1.3 for the final year. At a close inspection, the growth levels have similar rates compared with those of chapter 5 respectively but estimated figures for 2013 to 2015 are proportionally higher, which may prioritize the adoption of this model in case global networking traffic is to increase excessively. Another observation that might be of interest comes from the AGR figures in which respective decay rates seem to slow down as they develop towards 2015, suggesting narrow AGRs close to just lower than

1.3 in the far future. Some average "guesstimates" for 2016 and 2017 have shown respective annual growth figures not to be lower than 1.27.

Year ε	Data Type	G.IP(ε) (PB/month)	AGR
2012	Forecast	37540	1.36
2013	Forecast	49899	1.33
2014	Forecast	65640	1.31
2015	Forecast	85487	1.30
Average estimated AGR 2012-2015			**1.325**
2016	Guesstimate	98000 - 119000	-
2017	Guesstimate	130000 - 149000	-

Table 30: Worldwide IP traffic forecasts

All the important findings are concisely formed into the next two graphical representations (figures 33 and 34). The connection of historical data with the proposed forecasts illustrates the capability of the model to maintain an excellent relation between the two distinguished timeframes: the past and the future. In addition, the annual growth rate tendency beyond 2011 is expected to produce accurate figures of no more than 10% associated prediction error.

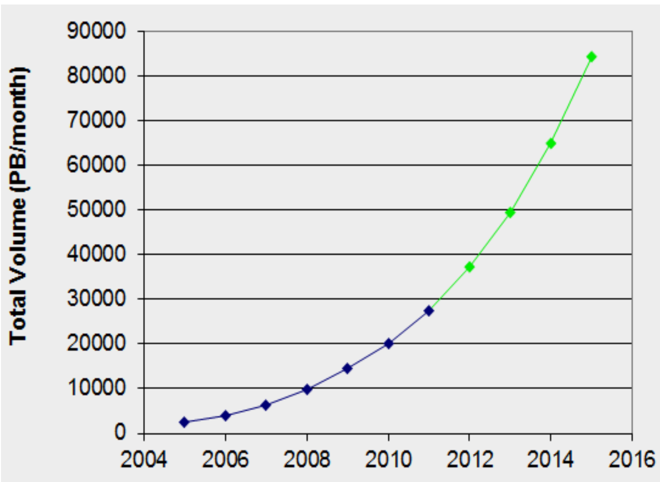


Figure 33: Real (blue) and estimated (green) IP traffic

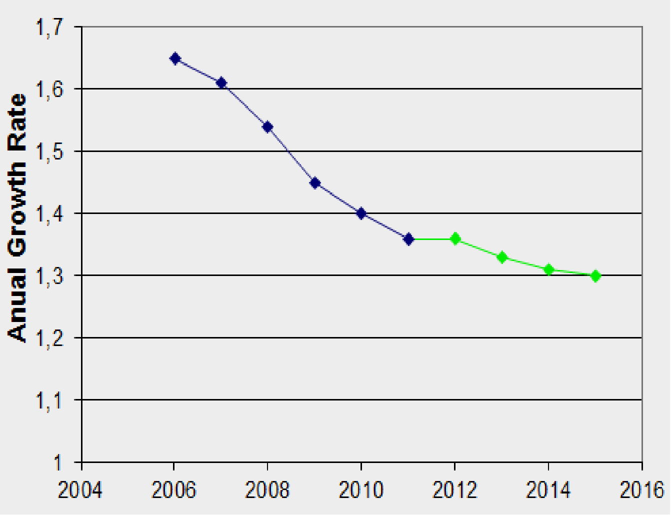


Figure 34: Historical figures (blue) and forecasts (green) of AGRs

6.7 Analysis and Alternative Scenarios

The empirical relation that has been produced in this chapter requires the presence of certain numbers which give detail to the shape and to numerical results. Apart from assigning additional dependence to history traffic, the not-so-exponential behavior of the model is justified with the inclusion of volumes G.IP(ε–1), G.IP(ε–2) and of fixed numbers 800 and 495. Those linear attributes provide reduced levels of sensitivity and particular detail to calculations using formula (67), which require small effort at the revising procedure (if necessary) in the near or far future. Specifically:

(i) Constants 800 and 495 can be replaced with a fixed range of numbers ΔF and ΔG respectively, e.g. at ±20% maximum of the original constants, which will be defined according to latest/updated trends. Within that range, further future projections should be as well accurate.

(ii) Large variations of ΔF and/or ΔG do not necessarily mean significantly different results as a whole and can be tolerated.

(iii) Even if the formula totally fails to predict traffic figures (far from 10% error), removing or adding extra parameters would not be required; only altering values of existing ones.

At its present format however, constants 800 and 495 seem to provide a good degree of stability to the slope of the equation and any varying levels of sensitivity that the exponent may add can be easily adjusted. Further numerical experiments suggest that if number 800 is slightly modified to some suitable range ΔF to be substituted in (67) to form a new equation (70), it can provide reasonable extrapolations of future traffic in a similar way that it does using the main equation of the previous chapter as demonstrated. Experimentations have also indicated that number 495 should remain intact and is to be changed only in combination with ΔF; this however is not advised as it would increase the complexity of the extrapolation procedure.

$$\mathrm{G.IP}(\varepsilon) = \mathrm{G.IP}(\varepsilon - 1) + \mathrm{G.IP}(\varepsilon - 2) - \left[(\varepsilon - 2008) \cdot (2^{0.65 + [0.25 \times (\varepsilon - 2008)]}\right) \cdot \Delta F + 495] \tag{70}$$

The most appropriate range for ΔF has been set to 700-900 which indicates some conservative projections of traffic for 2012 to 2015. Even more conservative figures are suggested within a limited range of 50 units and specifically if ΔF = 851 to 900. This limitation might be the most suitable in case the anticipated traffic of the future requires the model to be revised downwards instead of upwards and is to be seriously considered. Graph 35 shows realistic extrapolations while figure 36 demonstrates the more conservative approach of the model compared to that of chapter five. In the former we observe the data points are located quite close within a narrow space for only 2012 and 2013 forecasts. The variability between the upper and the lower limitations of the graph tends to be more obvious for periods 2014 and 2015 which is reasonable because of the proliferation characteristics of the term that contains the exponent.

On the other hand, figure 36 emphasizes variabilities of ΔF that affect each of the two models in a different way. We observe how a mere change of only 10 units can significantly affect the proposed future figures produced by the first model, while an absolute change of 200 units is less sensitive to the shape of the second proposed formula. For both cases, however, the proportional variance of the upper and lower boundaries seems to be clearer for 2014 and 2015, where data pairs exhibit higher levels of dispersion.

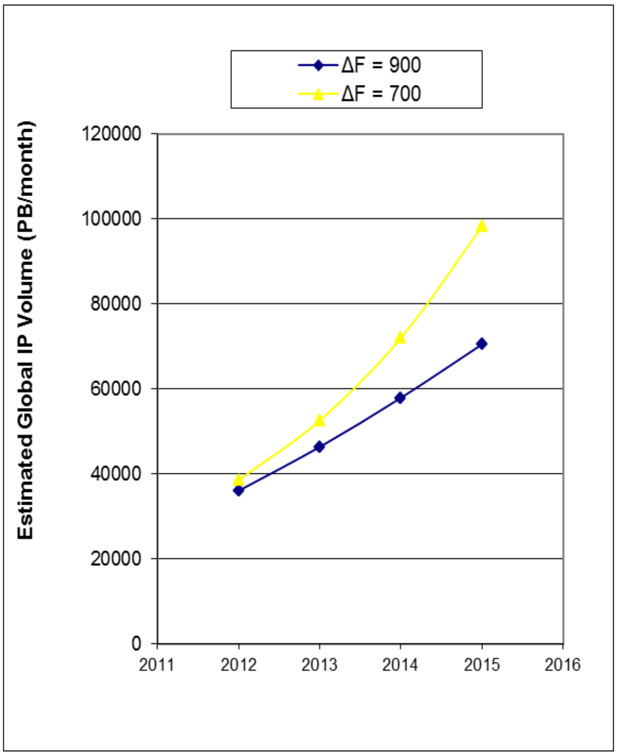


Figure 35: Extrapolating global IP traffic: 2012-2105 estimates

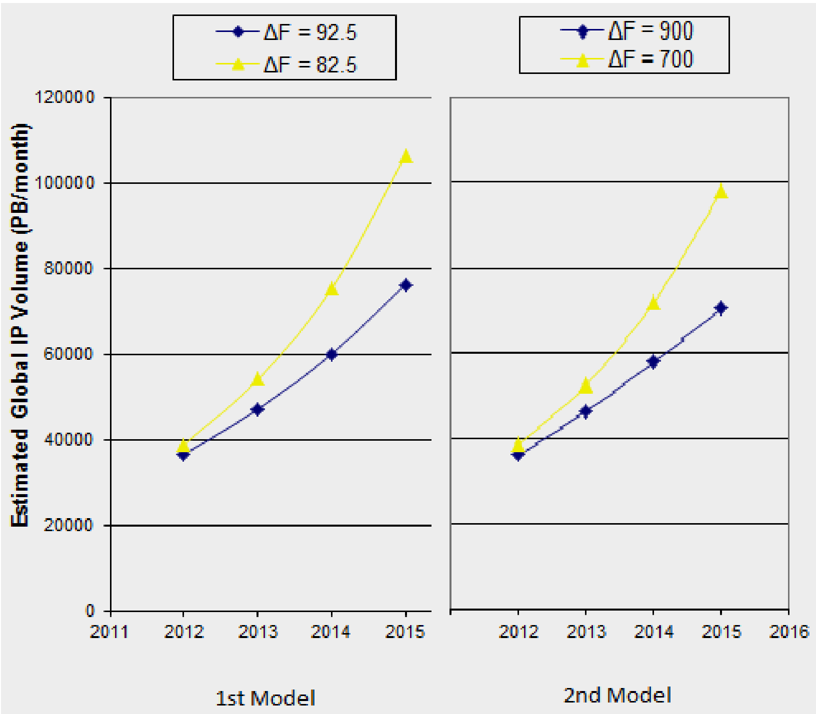


Figure 36: Range of extrapolations: Formula 49 (left) vs. Formula 70 (right)

Also worth mentioning is the fact that both the sensitivity and variability of the proposed methods are almost absent for 2012 projections, as shown in figure 36, to be located just below 40000 PB/month for both models. In each of those two graphs the difference between the lower and higher ΔFs for 2012 is not more than 3000, while for year 2014 the same difference has already expanded to at least 24000 PB/month. This feature seems reasonable in the way that near-future revisions and improvements tend to be more stable than the long run updates. By the time when certain revisions are proposed – if applicable – the best way to start is to focus on the first year ahead which may be the key to proceed further ahead. In other words, if predictions that have been made for the first year fail then the associated risk is getting higher for the second and the third year, due to the long-time uncertainties.

6.8 Evaluating Forecasts

Actual data for 2012 up to 2014 have now become available and in this way the accuracy of the model can be tested and further advice can be offered for future improvements, if necessary. Relation (67) produces an average forecasting error of 5.67% (table 31) which falls within the proposed range defined at less than 10% and therefore prediction attempts using the respective mathematical formula are considered successful.

Year ε	**Projected G.IP(ε)** (average PB/month)	**Actual G.IP(ε)** (average PB/month)	**Prediction error (%)**
2012	37540	38300	1.98
2013	49899	47400	5.27
2014	65640	59800	9.77
2015	85487	Not available	-
Average prediction error (so far)			**5.67**

Table 31: Evaluation results

When comparing prediction figures between universal equations (45) and (67), the former has an ideal error rate (<5%) while the latter slightly exceeds the corresponding

5% limit. Therefore, the first model is preferred to the second but both can be employed to offer reliable projections. However, equation (67) seems to be more prone to errors as time reaches year 2014 as illustrated in table 31. In particular, the rate has increased to more than 3 percentage units from 2012 to 2013 and another 4.5 units from 2013 to 2014. Should the value continue to grow at this fast pace, then the model is definitely not reliable for estimating 2015's traffic and must be extensively revised to be seriously considered for further predictions beyond 2015. Even if data for 2015 are still pending and in spite of its very good predictability, the formula is almost certain to fail to project a further 3-year timeframe traffic at its current format. At this point it must be reminded that successful predictions mean an average associated error of less than 10% and any suspicion of producing a rate other than that must be excluded – not only for this thesis but for similar future work as well. Figure 37 clearly demonstrates the tendency of the second model to magnify its dispersion through time against the first and the already available new data. The very small gap between all figures is present only in the first year of estimates; further ahead it tends to increase, albeit not out of bounds for the data we have so far.

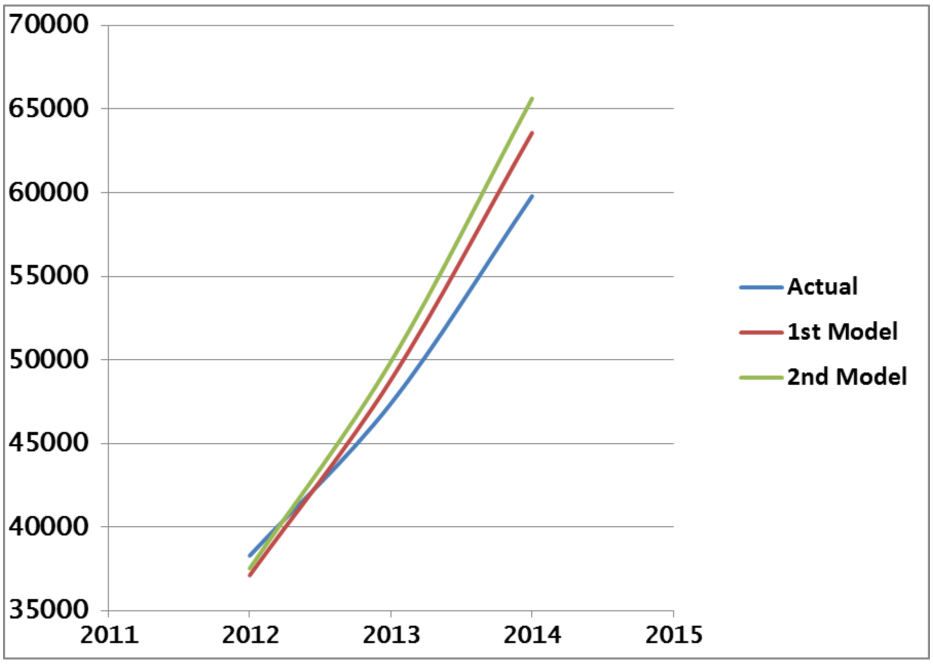


Figure 37: Progression properties of the proposed estimates vs. new traffic data released

Finally, results from table 31 are strong evidence to an issue that has already been raised: it is of outmost importance that future estimations should be conducted for no more than three years ahead. If projections for 2015 fail, it is because the 3-year forecast horizon, as proposed, has been exceeded by the time the studies have been made. This is an essential conclusion which is once more confirmed – but has already been proved in previous chapters, especially with Cisco Systems' estimates – and, in my opinion, must be always regarded as the first and basic rule for long-time Internet traffic forecasts. A violation of the rule will not necessarily mean inaccurate results but the risk of adding further years can lead to extremely huge error rates, which should not be an option for high level studies.

CHAPTER 7

Future Projections of Global Internet Users

"Two things are infinite: the Universe and human stupidity; …and I am not sure about the Universe"

- Albert Einstein

Studies in this chapter are focused on historical numbers of Internet users in the world to make estimations on their future growth. The historical trend of pertinent data has ideal numerical properties and the proposed formula has an excellent potential to predict total users in the next years. So far, the model has a forecasting error rate of only 1.5%.

7.1 Global Figures for the Total Number of Users

Historical data for global IP and fixed traffic volumes seem to be available from only one source, Cisco Systems, as cited throughout the thesis. For Internet users, however, there are several reports that exist on the Web [Stat2015], [Iws2015], [Ils2015], including the International Telecommunications Unit (ITU) [ITU2015]. Some of them contain statistics not only for the total global figures but over different regions and countries too, as well as by other categories, e.g. users' gender, users by connection type (fixed, mobile) etc. Certain reports also provide some estimates for the future, however the method that has been used is not specified. Of most important note is the fact that none of them has exactly the same historical information for the same years, when compared to the other reports, but all figures seem to have the following in common:

(i) The number of Internet users increases every year in certain countries and globally. Figures may vary between developed and developing countries.

(ii) The rate of the annual growth for respective years is almost the same in all reports for the last several years.

(iii) The pace of growth is smooth, i.e. there are no extreme spikes or fluctuations.

Observations (i) to (iii) means they can be effectively used for predictions, ideally by producing a suitable formula, even though their historical data have some small differences. For example in [Stat2015] it is reported that global users in 2014 had reached 2.94 billion, which is almost the same with the ITU historical figures at 2.937 billion [ITU2015], while for the same year a different source claims total users were as high as 3.079 billion [Iws2015]. Those variations can have a maximum deviation in the order of 100 million users but the relative difference is calculated at around 3.5% only, which is far better than the level of variation between the two sources of fixed Internet traffic statistics, as presented in the literature chapter. Even if differences between the three reports above were to be significantly larger (e.g. 10-15%), the fact that observation (ii) is consistent would balance the negative implications of large levels of variation. Table 32 and graph 38 illustrate aggregate figures of global Internet users.

Developed/ Developing Countries	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015*
Developed	616	649	719	753	776	824	841	921	961	997	1035
Developing	408	502	645	808	974	1195	1383	1573	1743	1940	2139
World	1024	1151	1365	1561	1751	2019	2224	2494	2705	2937	3174

Table 32: Historical numbers of global Internet users in millions (*estimates) [ITU2015]

In table 32 and after 2007, we observe the higher figures are coming from developing regions rather than from developed countries; calculations on annual growth rates are also proportionally higher. This is a further evidence of the larger AGRs of the developing world, this time for the global users, when they are compared to the respective rates of the rest of the world. This persisting trend comes from the most populous countries around the world, mainly in the Asia & Pacific region but in Latin America as well. As with Cisco's figures presented in earlier chapters, maybe the larger growth coming from those continents will continue in the near and maybe the far future too. From a global view, the penetration rate of users related to the global population has reached 40.6% in 2014 and it is estimated that this rate will increase to 43.4% in 2015 [ITU2015].

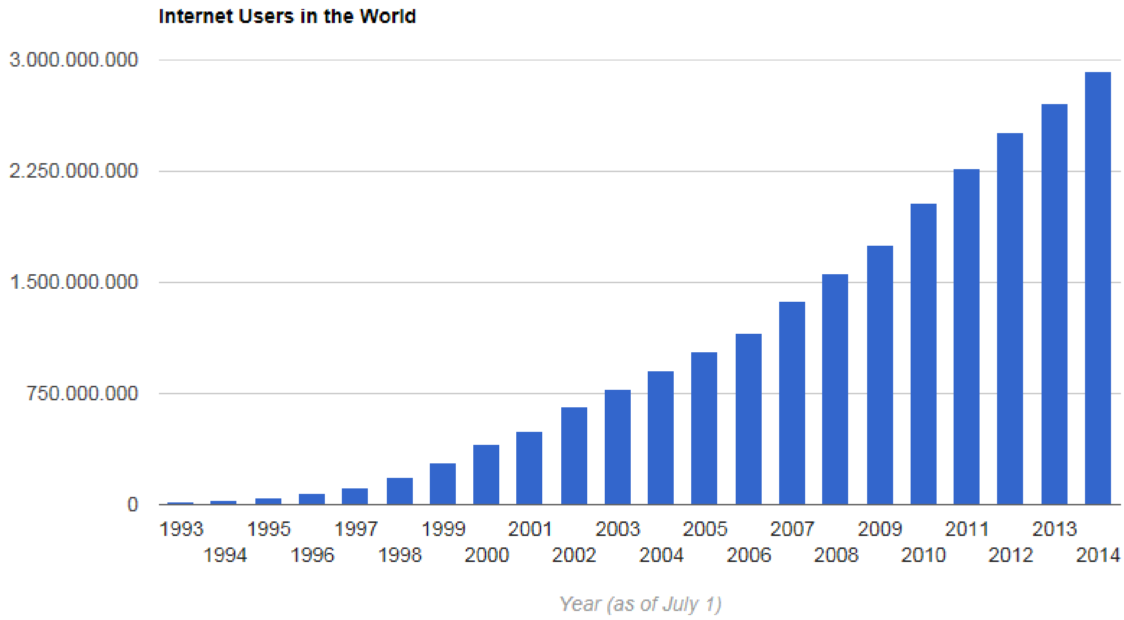


Figure 38: Progression properties of Internet users [Ils2015]

Graph 38 shows yearly figures growing at a smooth rate and further statistics in table 33 confirm this stable pace as chronologies progress towards 2014. The latter provides more detail of how the number of users has grown in between a 3 to 6 months interval (apart from year 2013) in which we can observe some slight seasonal inconsistencies. The total number of users by the end of each year will be considered to investigate fitting properties, detect patterns and form a suitable relation for predictions. Table 33 has been taken from a more enlarged data set, listing the total number of users since 1995, and all details can be seen in [Iws2015]. At this point it should be also noted that annual growth rates have been calculated using the information after 2005. In most cases the computed AGRs from users have similar trends with respective global IP traffic AGRs and, specifically, both are declining at a stable pace. This observation is extremely important because:

(i) The similarity of their properties suggest that there is a formula capable of relating Internet users for a given year to the year before – exactly the same assumption as with both global IP equations presented in previous chapters. The new proposed users' formula should be of an exponential-like form as well, exhibiting certain similarities with variables and constants proposed for the global IP formula and the Amsterdam IXP equation.

(ii) Both users and Internet Protocol traffic represent the worldwide activity on the entire Internet. Finding a relation between them can expand our understanding on how traffic can be expressed as a function of the number of Internet users and vice versa. This suggests a strong connection of historical behaviour of users with the historically generated IP aggregate traffic.

Case (ii) should clearly indicate a connection of the average traffic share per each individual. Both (i) and (ii) are indeed the subject of this chapter and are presented immediately in the sections that follow.

Date	Numbers of Internet users (in millions)	Percentage of global population	Source
Dec, 2008	1574	23.5 %	Internet World Stats
Mar, 2009	1596	23.8 %	Internet World Stats
June, 2009	1669	24.7 %	Internet World Stats
Sept, 2009	1734	25.6 %	Internet World Stats
Dec, 2009	1802	26.6 %	Internet World Stats
June, 2010	1966	28.7 %	Internet World Stats
Sept, 2010	1971	28.8 %	Internet World Stats
Mar, 2011	2095	30.2 %	Internet World Stats
Jun, 2011	2110	30.4 %	Internet World Stats
Sept, 2011	2180	31.5 %	Internet World Stats
Dec, 2011	2267	32.7 %	Internet World Stats
Mar, 2012	2336	33.3 %	Internet World Stats
June, 2012	2405	34.3 %	Internet World Stats
Sept, 2012	2439	34.8 %	Internet World Stats
Dec, 2012	2497	35.7 %	I.T.U.
Dec, 2013	2802	39.0 %	Internet World Stats
June, 2014	3035	42.3 %	Internet World Stats
Dec, 2014	3079	42.4 %	Internet World Stats
June, 2015*	3270	45.0 %	Internet World Stats

Table 33: More detailed figures of global users (*estimates) [Iws2015]

7.2 Definition and Significance of Predicting Users' Figures

An Internet user is referred to the person who can access the Internet either via a computer device or some mobile equipment within the home of residence of that person [Ils2015]. There are certain ITU guidelines to collect data for users in different countries. The method of collection may include household surveys and some examples on definitions and questionnaires for that purpose are available from an ITU manual in [ITU2014]. From the information we have from global statistics so far, it seems easier to record data on Internet users rather than monitoring and measuring the associated global traffic. For the former, the collection of pertinent data seems to be more transparent and obvious whatsoever; the publicized figures, albeit from different sources, have a very good match. Most of the currently available historical information for users that exists on the Web can be used for thorough detection of patterns and reveal progression properties in the last several years, since they have minor differences. They all satisfy the defined criteria of chapter three and, moreover, they display very small fluctuations when carefully observed.

Table 33 has been initially selected to investigate hidden properties in the numbers as they appear in chronological order. It is absolutely important that a rigorous formula is produced to characterize and project users' behavior in precise figures. The enormous usage of video and audio related services as well as peer-to-peer activities has a strong impact on global volumes flow, as described in existing work. Another fine example is the increase in UDP traffic in the last years and this is also caused by P2P traffic [John2010]. Apart from certain automated processes, most of the activity on the Internet originates from people using it, therefore we must know how they are likely to advance in the long term (1st proposed equation, this chapter) and then connect them with the global traffic volumes (2nd proposed equation, next chapter). The investigation excludes the use of penetration rates (column 3, table 33) for the involved experiments, mainly because global population figures must be studied separately using non-technical aspects such as from a social, economic and/or medical-oriented perspective.

7.3 Detecting Numerical Properties

Historical data since 2005 up to the latest available (end of 2014) are scrutinized to form the progression properties. Again for this stage it has been investigated whether a relation of an exponential form can be found, although as with all data in this thesis equations are not strictly exponential. At this point it shall be reminded that producing an exponential-like formula has certain advantages including necessary updates for the future. To this extend, we proceed including all pairs of historical numbers of global (G) Internet users (Iu) for years Ɛ and Ɛ−1 by looking for a universal relation of the following expression:

$$G.Iu(\mathcal{E}) = [G.Iu(\mathcal{E}-1)]^{P} \qquad (71)$$

Format of (71) is consistent with the corresponding global IP traffic (G.IP), however the power as a function of P is different when including year Ɛ. First, all years have been consecutively observed for respective pairs starting from 2005. Considering the whole decade 2005-2014, trends for the first three years (2005 to 2007) tend to have some slightly different properties when compared to the rest of the period (2008-2014). Thus it is wise to exclude them at this stage to avoid large levels of fitting errors. The selected timeframe for 2008 to 2014 has no particular peculiarities, apart from one single spike which is of low level. This variation can be effectively managed by the experimentations settings without really affecting the procedure all together. For all the suitable history of Internet users, the following relations are the available pairs for the global number of users (in millions) to reveal the still unknown P:

$$G.Iu(2009) = [G.Iu(2008)]^{P1} \Rightarrow 1802 = 1574^{P1} \quad (72)$$

$$G.Iu(2010) = [G.Iu(2009)]^{P2} \Rightarrow 2040 = 1802^{P2} \quad (73)$$

$$G.Iu(2011) = [G.Iu(2010)]^{P3} \Rightarrow 2267 = 2040^{P3} \quad (74)$$

$$G.Iu(2012) = [G.Iu(2011)]^{P4} \Rightarrow 2497 = 2267^{P4} \quad (75)$$

$$G.Iu(2013) = [G.Iu(2012)]^{P5} \Rightarrow 2802 = 2497^{P5} \quad (76)$$

$$G.Iu(2014) = [G.Iu(2013)]^{P6} \Rightarrow 3079 = 2802^{P6} \quad (77)$$

Common parameter P has decaying characteristics observed over all variables from P1 to P6 as corresponding years increase from 2009 to 2014, apart from P5. The size of the proposed P_i‘s (index i = 1 to 6) is to indicate an explicit relation in the exponent; firstly, we use the common logarithm properties to calculate values for respective P_i‘s and results are as follow:

Relation	Value of P_i
$1802 = 1574^{P1}$	1.018377
$2040 = 1802^{P2}$	1.016548
$2267 = 2040^{P3}$	1.013845
$2497 = 2267^{P4}$	1.012507
$2802 = 2497^{P5}$	1.014731
$3079 = 2802^{P6}$	1.011876

Table 34: Range of P

The low fluctuation that P5 displays is not a barrier to come up with ideal fitting values for all parameters. If there were more such fluctuations exhibited from other P_i's too, only then it could be regarded as an undesired phenomenon. This is just an isolated characteristic and shall not affect the next stage; the rest of the numbers have a smooth progression over the included timeframe. Some considerable deviation of a single variable is manageable provided that the calculated average is generally low for the whole procedure. Even if the mean fitting error is higher than expected, e.g. higher than respective calculations for the formulae in previous chapters, it should successfully indicate future figures.

7.4 Trend Characterization and Proposed Relation

Numbers in column 2 (table 34) are to be used for numerical experiments. Their minimum to maximum value and the average declining rate over the whole range will suggest alternative values that have suitable characterization properties. Not surprisingly, the peculiarity of exponent P5 has caused some variations to new fitting exponents P3, P4 and P5 related to the actuals, however all results produced at this stage are almost ideal. A fine range of experiments has suggested that it is possible to balance the low-level influence of P3 to P5 and, after an extensive set of computations, the selected figures for P1-P6 (table 35) seem to have the lowest fitting error over the actual values of table 34. All fitted results are rounded to the closest integer and the yearly percentages are to the second decimal digit. At the same time, the numerical progression shape of the new proposed P can be easily used to form an appropriate equation to make predictions, since the declining rate of P has been selected at 0.0014 year over year.

Year ε	Proposed P	Fitted G.Iu(ε) (millions)	Actual G.Iu(ε) (millions)	Fitting error (%)
2009	P1 = 1.0180	1797	1802	0.28
2010	P2 = 1.0166	2041	2040	0.05
2011	P3 = 1.0152	2291	2267	1.06
2012	P4 = 1.0138	2522	2497	1
2013	P5 = 1.0124	2751	2802	1.82
2014	P6 = 1.0110	3058	3079	0.68
Average fitting error				**0.815**

Table 35: Summary of fitted vs. actual data

The low average rate at 0.815% is indeed excellent. It can be interpreted as being an ideal figure to proceed to future estimations, thus the soon to be proposed formula is expected to produce forecasts at a very good precision rate. The following figure shows an excellent match between the actual and fitted data. The model has an excellent prospective to maintain the current trend for the next three years.

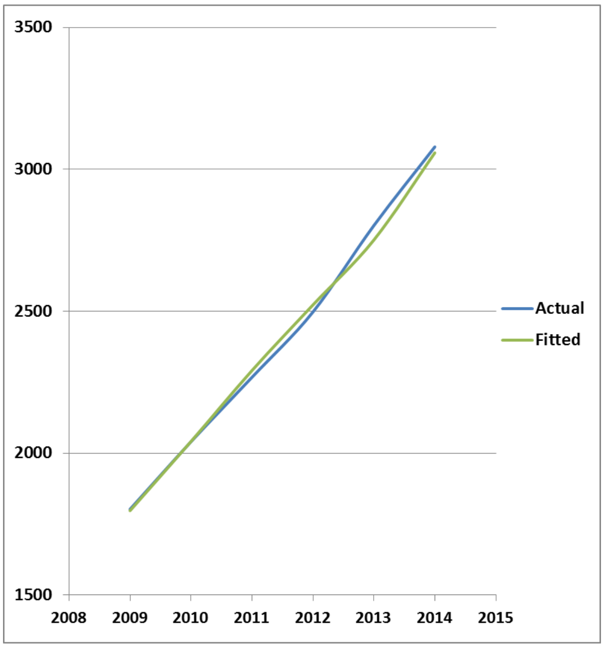


Figure 39: Real and proposed fitted figures for global Internet users (in millions)

Although the fitting stage has not allowed for much flexibility, it has clearly indicated that the associated fixed declining rate at –0.0014 shall be applied to each year. The combination of the progression rate with the range of P for respective years can be observed through the following explicit relations:

Year 2009: $[180 - 14\cdot(0)]/10000 + 1$ (78)

Year 2010: $[180 - 14\cdot(1)]/10000 + 1$ (79)

Year 2011: $[180 - 14\cdot(2)]/10000 + 1$ (80)

Year 2012: $[180 - 14\cdot(3)]/10000 + 1$ (81)

Year 2013: $[180 - 14\cdot(4)]/10000 + 1$ (82)

Year 2014: $[180 - 14\cdot(5)]/10000 + 1$ (83)

As a result, exponent P including year ε is modified accordingly and the final equation is of the following expression, with restrictions (85) and (86) to apply as necessary:

$$G.Iu(\varepsilon) = G.Iu(\varepsilon - 1)^{\frac{180-14(\varepsilon-2009)}{10000}+1} \tag{84}$$

$2009 \leq \varepsilon \leq 2014$, fitting stage (85)

$2015 \leq \varepsilon \leq 2018$, future projections (86)

7.5 Expected number of Internet Users for 2015 - 2018

The shape of equation (84) is similar to that of Amsterdam IXP traffic but different than the other two for the global IP part. However, prediction attempts using this function are as well expected to be accurate for at least three years (2015-2017) and maybe for 2018 if trends do not significantly change. According to relation (84), the total number of global users we expect for the next four years are as shown in table 36.

Year ε	**Data type**	**G.Iu(ε)** (millions)	**Annual Growth Rate**
2015	Forecast	3326	1.08
2016	Forecast	3555	1.069
2017	Forecast	3758	1.057
2018	Forecast	3929	1.046
Estimated Average AGR			**1.063**

Table 36: Future estimates for Internet users for the entire world

Additionally, the next two figures show trends of the past and for the future as expected. We can clearly observe similar tendencies between the main two timeframes.

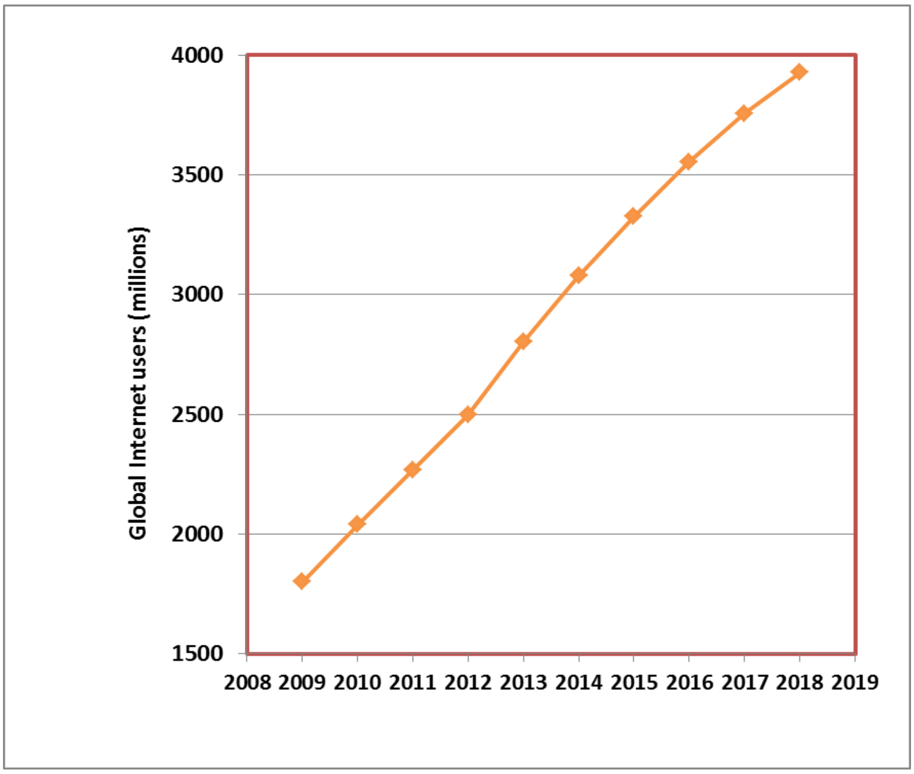


Figure 40: Historical (2009-2014) and expected (2015-2018) number of users

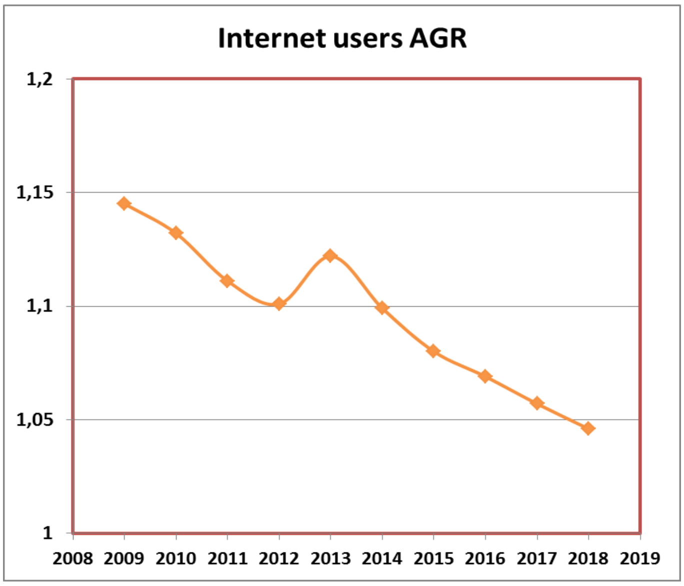


Figure 41: Historical (2009-2014) and expected (2015-2018) corresponding AGRs

However, the annual growth rate for year 2013 is slightly different than the rest of the shape due to the irregularity of the proposed exponent P5, as discussed previously. This reasonable characteristic does not in any way affect the whole trend which, if maintained, can indicate future number of users with a very good precision.

Figures in table 36 suggest a wide range of growth in the number of users from 150 to 250 million per year but an almost fixed rate of respective annual growth at –0.011 year over year. This may be convenient in the way that if the trend continues at a stable pace, the predictability of the model would have excellent results even in the very far future. It would be also ideal for ISPs and large networks to have some macroscopic certainty for the purpose of technical and investing purposes. However, Internet users are part of the total population of the Earth and the rate at which they penetrate the global population seems to be growing at a stable speed. In table 33 one may observe the penetration rate adds around 3 percentage units at a year over year level and it has already reached near the half of the total population. But for how long can the penetration growth be sustained at that rate?

According to some calculations using the figures of table 33, annual population growth rate alone is slower than the users' penetration growth rate. The latter is increasing fast anyway and this may imply that saturation should be expected at some time, e.g. at penetration rates of maybe 80% or more. This fact must be also investigated in terms of global population growth and ideally with producing some long term forecasts for the whole planet's population. This proposal is not a subject of the present thesis but can be certainly referred for future work and in collaboration with other suitable fields, e.g. social, medical and environmental studies. However, Internet users' growth can be effectively studied in terms of how they are related to the corresponding traffic that they generate: the global IP traffic. This project is a subject of investigation in chapter eight.

7.6 Evaluation

At present there is only one source that has released actual Internet users' data for 2015. As of 31st December of 2015, the users' clock embedded in [Ils2015] has displayed a total number of approximately 3.277 billion (3277 million) of global Internet users. The International Telecommunications Unit [ITU2015] and the Internet World Statistics [Iws2015] have provided their estimates for the end of 2015 but without including the actual figures for 2015. Again using equation (5) from section 2.9, forecasts come with an exceptional error rate as low as 1.5%. However, the only available figure is that of 2015 (table 37) and, as with some other evaluations in earlier chapters, the total average rate will be calculated at the end of the proposed prediction timeframe.

Year ε	**Estimated users G.Iu(ε)** (millions)	**Actual users G.Iu(ε)** (millions)	**Prediction error (%)**
2015	3326	3277	1.5
2016	3555	Not available	-
2017	3758	Not available	-
2018	3929	Not available	-
Average prediction error (so far)			**1.5**

Table 37: Evaluation results of the proposed formula for global users

ITU's estimates for the global Internet users as presented in [ITU2015] and those of the Internet World Statistics [Iws2015], both for 2015, have a slightly higher prediction error when compared to the estimated figure of table 37. However, both have predicted very accurately as their error percentage is as well below 5%.

CHAPTER 8

Connecting Global IP Traffic with Global Users

"Ego = Knowledge $^{-1}$: more the knowledge lesser the ego, lesser the knowledge more the ego"

- Albert Einstein

In this chapter, the worldwide historical trends of Internet users and that of IP traffic will be used to reveal any connection between them. Since the available history figures are now different with those that have been used for the IP traffic studies, the proposed formula should be able to indicate future figures with even greater precision.

8.1 Reasoning

Studies in chapters 5, 6 and 7 make use of the largest and most representative sample of historical information: the global data. Furthermore, investigations in those chapters are not only based on the totality of the information but on figures of which IP traffic has been generated by the users. This means the total IP traffic should be related as a function of the total number of Internet users, which have actually caused most of the traffic. Thus, we are now looking for a relation to be expressed with the following proposed format, where G.IP(ε) is the global IP traffic and G.Iu(ε) is the number of global users:

$$\mathrm{G.IP}(\varepsilon) = f[\mathrm{G.Iu}(\varepsilon)] \tag{87}$$

However, certain issues may affect the quality of the proposed investigation and the following questions are therefore raised:

(i) Which of the available historical data for Internet users should be selected?

(ii) Why does equation (87) propose IP traffic as a function of users of the same year, rather than of previous year as with all formulae so far?

The answer to the first question is quite obvious, since the data to be used have to be the same with chapter 7, mainly for consistency reasons. But even if another set was to be considered, it is not supposed to seriously affect the experimentations since there are only minor differences. About (ii), recorded data of users can be effectively linked to the same period of the total generated IP traffic only, i.e. for the same reference year. All formulae so far relate sizes to previous years but this is because they always refer to the same category, while for this part we have two different types of investigation. Apart from that, another important reason is the large level of inconsistency found for figures in $G.IP(\varepsilon)$ as a function of those of previous years $G.Iu(\varepsilon-1)$. Medium to strong levels of spikes and fluctuations have been observed, implying that any attempt relating the two aforementioned sizes will probably be invalid.

In contrast, a thorough observation of all included sets $G.IP(\varepsilon)$ and $G.Iu(\varepsilon)$ for the same chronologies have revealed an explicit and rigorous pattern for ten consecutive historical years. This is the only chapter that makes full use of all historical data for the whole decade 2005-2014, whereas in other projects certain years have been excluded due to inconsistencies. By bookkeeping relations, it has been observed that a persistent numerical property is present to all pairs between $G.IP(\varepsilon)$ and $G.Iu(\varepsilon)$ in the last ten years and this can be well represented with a further parsimonious equation. Furthermore, another reason for selecting (87) can be attributed to the fact that statistics for Internet users seem to be released faster than the measurements for the IP volumes. In this way, relation (87) might be the only option for estimating unknown IP traffic immediately after the data for users have become available, instead of anticipating them from the original source. In fact, it looks like there is a “users clock” in [Ils2015] embedded within the statistics webpage which counts existing Internet users around the entire world and displays them in real time. This useful feature may be a good alternative for making predictions on global IP traffic in case the latter is still pending.

8.2 Data Observation

All historical information for the totality of IP traffic and Internet users have been put into in-depth analysis. First, global figures in tables 22 and 26 will be compiled into one, to form the historical IP volumes for the last decade, 2005-2014 inclusive. The enlarged version of table 33, which is available at [Iws2015], is to further include years 2005 to 2007. Thus, any numerical properties can be detected easier when all the information is merged into the following single table:

Year ε	G.IP(ε) (average PB/month)	G.Iu(ε) (millions)
2005	2426	1018
2006	3992	1093
2007	6430	1319
2008	9927	1574
2009	14414	1802
2010	20197	2040
2011	27483	2267
2012	38300	2497
2013	47400	2802
2014	59800	3079

Table 38: The entire historical traffic generated by respective users

As with all data sets, we look for hidden patterns between consecutive pairs. This time, figures G.IP(ε) and G.Iu(ε) for the same years will be observed, instead of looking for a relation between data from years ε and ε−1. The fact that all information for the same years is applicable for this chapter only, suits with the discovery of an explicit relation revealed by the data of table 38. Through careful observation, it has been concluded that an exponential-like equation is not the best option for this data set, but a formula of some other algebraic form would be more reliable. But why is a non-exponential format more suitable for this situation?

When observing consecutive data between all years ε and ε−1, the produced relation tends to be exponential, albeit not a strict one. However, when looking at pairs for the same years ε – of which there are already exponential equations proposed – we actually try to find an association between two exponential representations. G.IP(ε) and G.Iu(ε) have been defined as exponential-like in respective chapters, consequently this assumption applies to both. This means results of certain operations between them can be of different form, such as their ratio which may be closer to a linear contribution. Therefore we need to verify or disprove this feature and, for this reason, the following two equations are considered to detect a suitable format for relation (87):

$$G.IP(\varepsilon) = [G.Iu(\varepsilon)]^{\chi(\varepsilon)} \quad (88)$$

$$G.IP(\varepsilon) = [G.Iu(\varepsilon)]\cdot[TUR(\varepsilon)] \quad (89)$$

G.IP(ε) and G.Iu(ε) are all available historical data for 2005-2014, χ(ε) is some exponent and TUR(ε) is the Traffic to Users Ratio defined as G.IP(ε)/G.Iu(ε) for all corresponding years ε. Proceeding to calculations of χ and TUR, the following table 39 includes the necessary findings.

Year ε	G.IP(ε) (PB/month)	G.Iu(ε) (millions)	X(ε) according to (88)	TUR(ε) according to (89)
2005	2426	1018	1.125	2.383
2006	3992	1093	1.185	3.652
2007	6430	1319	1.22	4.875
2008	9927	1574	1.25	6.307
2009	14414	1802	1.277	8
2010	20197	2040	1.301	9.9
2011	27483	2267	1.323	12.123
2012	38300	2497	1.349	15.338
2013	47400	2802	1.356	16.916
2014	59800	3079	1.369	19.422

Table 39: Exponential and linear relation assumptions

The first main observation from table 39 is the strict ascending order of all numbers in the last two columns. It seems either is suitable but certain peculiarities of their patterns have suggested that Traffic to Users Ratio is preferred over $\chi(\varepsilon)$.

8.3 The Fitting Stage

The next and most important step is to select the data set of the column for which well-suited proposed values will have the lowest error rate and according to the ability to sustain the associated trend beyond 2014. After an extensive set of numerical experiments, alternate numbers for all χ and TUR of table 39 have been assigned to indicate their level of effectiveness. In general, the proposed numerical ranges for both $\chi(\varepsilon)$ and $TUR(\varepsilon)$ have a very good response towards the actual data, but numbers for TUR are slightly better in terms of fitting error and low complexity to form an equation. Furthermore, the proposed exponents for all χ display several low-level fluctuations related to the actual while, on the other hand, alternative $TUR(\varepsilon)$ variables are quite consistent on average. Thus, equation (89) is more appropriate and has been selected over (88). Traffic to Users Ratio will be defined in more detail in the next section, together with the overall proposed format of (89).

In table 40, the associated error rates have been calculated using the same method as with all respective fitting procedures. Equation (89) calculates $G.IP(\varepsilon)$ for all new proposed $TUR(\varepsilon)$, while the number of users $G.Iu(\varepsilon)$ is always the actual figure for corresponding year ε (column $G.Iu(\varepsilon)$ in table 39). New figures for $G.IP(\varepsilon)$ are then compared to the actual values, from which the respective fitting errors are computed; the whole procedure and results are summarized in table 40. We can observe excellent rates for most of the fitted data apart from the percentages of two years, for 2005 and 2012, which derive from reasonable deviations but are nevertheless acceptable. The average rate calculated at only 1.79% demonstrates the goodness of the proposed model over the total historical timeframe.

Year ε	Actual G.IP(ε)	Actual TUR(ε)	Proposed fitted TUR(ε)	G.IP(ε) according to the proposed fitted TUR(ε)	Associated fitting error (%)
2005	2426	2.383	2.5	2545	4.91
2006	3992	3.652	3.6	3935	1.43
2007	6430	4.875	4.9	6463	0.51
2008	9927	6.307	6.4	10074	1.48
2009	14414	8	8.1	14596	1.26
2010	20197	9.9	10	20400	1
2011	27483	12.123	12.1	27431	0.19
2012	38300	15.338	14.4	35957	6.12
2013	47400	16.916	16.9	47354	0.09
2014	59800	19.422	19.6	60348	0.92
Average fitting error					**1.79**

Table 40: Real and fitted data

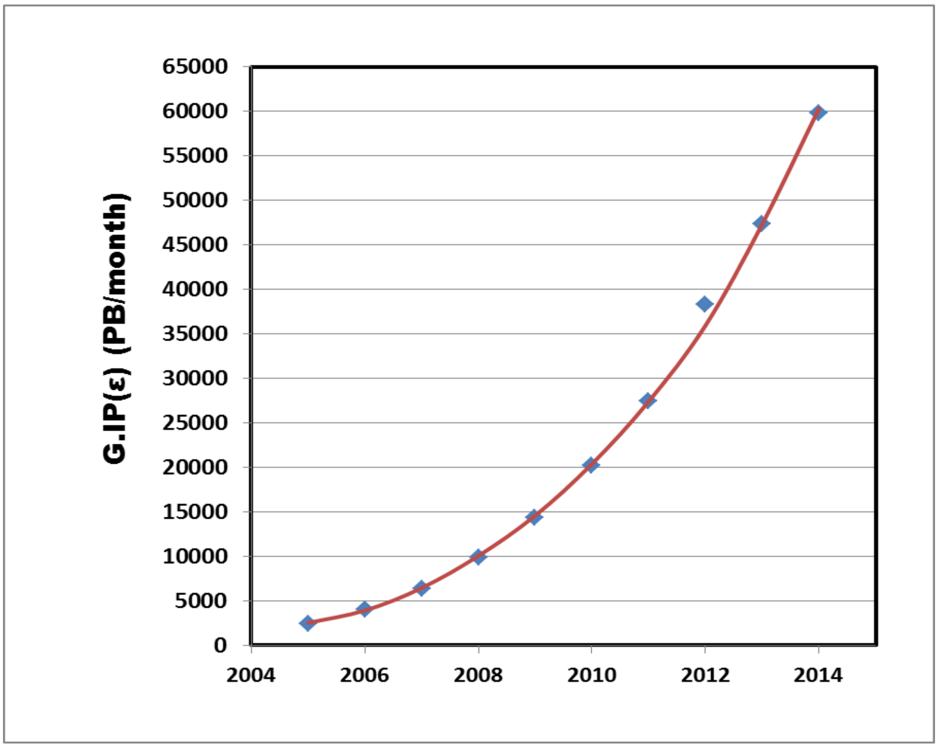


Figure 42: Actual (blue dots) and proposed fitted (red curve) data for global IP traffic

As a further evidence, figure 42 demonstrates the exceptional ability of the model to locate alternative data points through years 2005 to 2014 using generic equation (89).

Analysis on numerical patterns suggests that future trends are highly likely to be a successful expansion of the historical figures, at least for period 2015 to 2017.

8.4 Towards the Final Layout

For the purpose of future projections, the proposed relation in (89) must be presented with more details to form an suitable formula. Again, the idea is to include a separate parameter for the year, to be substituted as appropriate, and any additional variables and/or constants with suitable operations according to the pattern. At this point, equation (89) must be used and all observations will be further broken down to smaller numbers using suitable arithmetical operations. The proposed fitted sizes for all associated TUR parameters of table 40 are now introduced instead of the real. Thus, we get the first set of the following relations:

$$G.IP(2005) = [G.Iu(2005)]\cdot[TUR(2005)] \Rightarrow 2426 = 1018\cdot 2.5 \tag{90}$$

$$G.IP(2006) = [G.Iu(2006)]\cdot[TUR(2006)] \Rightarrow 3992 = 1093\cdot 3.6 \tag{91}$$

$$G.IP(2007) = [G.Iu(2007)]\cdot[TUR(2007)] \Rightarrow 6430 = 1319\cdot 4.9 \tag{92}$$

$$\ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots$$

$$G.IP(2014) = [G.Iu(2014)]\cdot[TUR(2014)] \Rightarrow 59800 = 3079\cdot 19.6 \tag{99}$$

A careful observation on the numbers of the proposed fitted TUR(ε) column 2.5 to 19.6 (table 40), indicate some value that is consecutively added to each number as these progress to 2014. At the same time and in every addition, the number increases at a constant rate of +0.2 starting initially at 1.1 for the first value of 2.5 (year 2005). This numerical pattern has not been too difficult to be observed, however the overall difficulty to form the final proposed equation is of medium complexity. Therefore, proceeding to the next stage, the right hand side of (90) to (99) can be replaced with the following relations arranged by their sizes:

$$2426 = 1018 \cdot 2.5 \Rightarrow 2426 = 1018 \cdot (2.5+0) \tag{100}$$

$$3992 = 1093 \cdot 3.6 \Rightarrow 3992 = 1093 \cdot (2.5+1.1) \tag{101}$$

$$6430 = 1319 \cdot 4.9 \Rightarrow 6430 = 1319 \cdot (2.5+1.1+1.3) \tag{102}$$

… … … … …

$$59800 = 3079 \cdot 19.6 \Rightarrow 59800 = 3079 \cdot (2.5+1.1+1.3+1.5+\ldots+2.7) \tag{109}$$

The fixed increase rate of +0.2 is added to ascending numbers 1.1 to 2.7, which can be written in more detail as we approach to find a suitable format for the universal formula. It is once again reminded, as with the whole thesis, that no software or any other form of mathematical or technical aid has been involved to reveal the observed numerical pattern. The procedure is based on pure observations on numbers and on bookkeeping all possible relations, for both the pattern detection and the equation forming. The following explicit multiplications have been carefully observed to effectively replace the steady 0.2 growth of several terms:

$$2426 = 1018 \cdot (2.5+0) \Rightarrow 2426 = 1018 \cdot [2.5+(1.0 \cdot 0)] \tag{110}$$

$$3992 = 1093 \cdot (2.5+1.1) \Rightarrow 3992 = 1093 \cdot [2.5+(1.1 \cdot 1)] \tag{111}$$

$$6430 = 1319 \cdot (2.5+1.1+1.3) \Rightarrow 6430 = 1319 \cdot [2.5+(1.2 \cdot 2)] \tag{112}$$

… … … … …

$$59800 = 3079 \cdot (2.5+1.1+1.3+1.5+\ldots+2.7) \Rightarrow 59800 = 3079 \cdot [2.5+(1.9 \cdot 9)] \tag{119}$$

Equations (110) through (119) can be ideally replaced by a fraction only for the ascending real numbers 1.0 to 1.9, which gives:

$$2426 = 1018\cdot[2.5+(1.0\cdot 0)] \Rightarrow 2426 = 1018\cdot[2.5+(1+0/10)\cdot 0] \qquad (120)$$

$$3992 = 1093\cdot[2.5+(1.1\cdot 1)] \Rightarrow 3992 = 1093\cdot[2.5+(1+1/10)\cdot 1] \qquad (121)$$

$$6430 = 1319\cdot[2.5+(1.2\cdot 2)] \Rightarrow 6430 = 1319\cdot[2.5+(1+2/10)\cdot 2] \qquad (122)$$

… … … … …

$$59800 = 3079\cdot[2.5+(1.9\cdot 9)] \Rightarrow 59800 = 3079\cdot[2.5+(1+9/10)\cdot 9] \qquad (129)$$

By applying the process of substituting all numbers that can be expressed as a function of the same year ε, two terms for each relation have been indicated as such. We now proceed to the broader format of (120) to (129) that connects global IP traffic with Internet users. Eventually, the final format of the proposed equation can now be expressed using (130):

$$G.IP(\varepsilon) = [G.Iu(\varepsilon)]\cdot[2.5+[1+(\varepsilon-2005)/10]\cdot(\varepsilon-2005)] \Rightarrow$$

$$G.IP(\varepsilon) = [G.Iu(\varepsilon)]\cdot[2.5+[(\varepsilon-1995)/10]\cdot(\varepsilon-2005)] \qquad (130)$$

To accord with the rest of the formulae presented in the thesis, there are two timeframes involved, thus the following restrictions must be considered:

$$2005 \leq \varepsilon \leq 2014, \text{ for historical figures} \qquad (131)$$

$$2015 \leq \varepsilon \leq 2018, \text{ for future estimates} \qquad (132)$$

The final relation of (130) could be further simplified; however it may be wiser to keep the present format to be consistent with the already proposed two formulae for G.IP(ε), presented in earlier chapters.

8.5 Comparison with Previous Models on Fitted Data

In previous chapters, both G.IP(ε) formulae have been expressed as a function of G.IP(ε–1), i.e. traffic as a function of some other traffic. In this study, inputs of G.IP(ε) always refer to Internet users G.Iu(ε) and at the same time the equation has linear contributions to the results instead of semi-exponential. With the exception of its linear characteristics, the way (130) is arranged in terms of parameter ε and variables/constants, it looks similar to the global IP formula (45) of chapter 5. The shape of (130) suggests even lower level of complexity when compared to that of relation (45) and, furthermore, it is far more simplified than the respective G.IP(ε) in equation (67) of chapter 6. The latter especially is an intricate version of (45), albeit effective, due to the numerous constants and the multi-presence of year ε. Furthermore, relation (67) combines the linearity of G.IP(ε–1) and G.IP(ε–2) with some medium-level of exponential influence due to an increased number of constants but at the same time it adds more detail to the result.

On the other hand, there is a significant lack of fitting data in equations (45) and (67). Due to the limited availability of recorded information when proposed studies on (45) and (67) were performed, their historical data timeframe had been extending to 2011 only, while equation (130) makes full use of period 2005-2014. Of more importance is the even narrower limitation of (67) which fails to take into account fitting properties before 2008 due to the restriction suggested by Euler’s method. As a result, the variation of the investigation period has inevitably led to some different predictions between (45) and (67) as already analyzed which, in turn, may (or may not) imply different forecasts using relation (130). However, the associated degree of deviation between all three models is totally insignificant when looking at the common historical period from 2008 to 2011 inclusive. The following graph visualizes their fitting performance for the common time periods only.

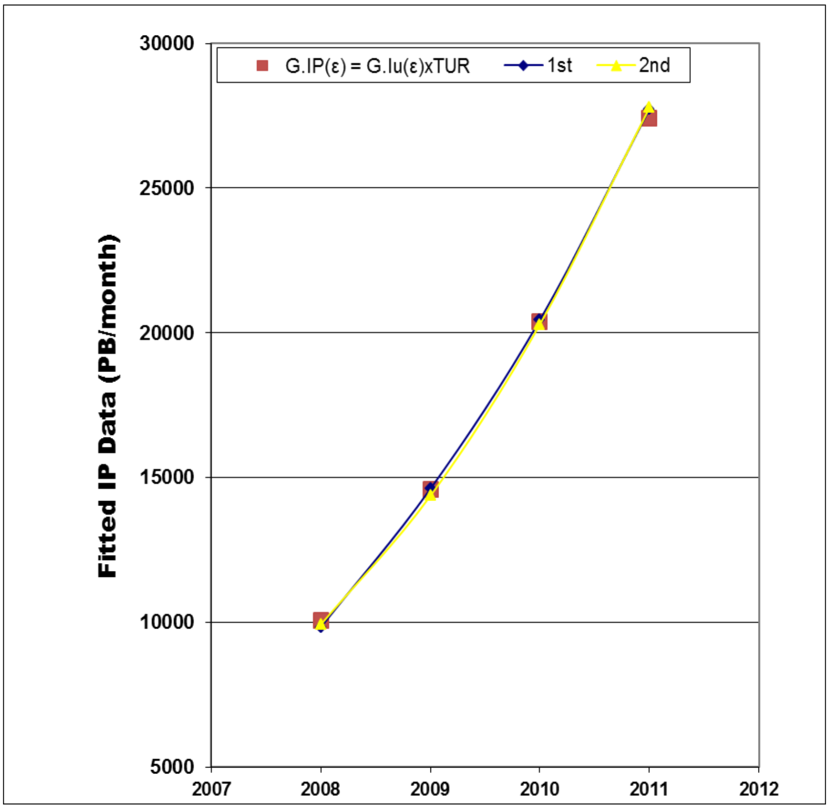


Figure 43: Overall demonstration of common fitted data between equations (45), (67) and (130)

We observe the fitting trend for the three proposed models is roughly the same. Calculations have indicated a maximum distance of ~2% between data for respective years and this can be further evidenced by comparing the 2012-2014 interval of historical figures for equation (130) with 2012-2014 forecasts for relations (45) and (67). Specifically, when looking at tables 40, 26 (chapter 5) and 30 (chapter 6) there are similar results in their corresponding 2012-2014 timeframe. However, figures in table 40 are closer to the actual which is reasonable because those studies have been conducted far more recently than the other two models. This fact is, once again, another confirmation for the importance of revising forecast models every three years in order to make predictions for the next proposed period, preferably for another three years. This means both formulae (45) and (67) must be re-considered and updated as appropriate to further estimate figures after 2015.

8.6 Projections of IP Traffic as a Function of Internet Users

As demonstrated, this model has a different functionality for data fitting and for the forecasting procedure as well. It uses data from respective global Internet users to predict IP traffic only for the same year ε. Therefore, it must be combined with results of G.Iu(ε) for which we expect for the future, as presented in chapter seven, and are available from table 36 produced by formula (84). In this way we substitute figures of users for years 2015 to 2018 (table 39) in equation (130) and obviously ε = 2014 to 2018 respectively. Results show expected global IP traffic as a function of users and can be viewed in the following table.

Year ε	**Data type**	**G.IP(ε) = *f*[G.Iu(ε)]** (PB/month)	**Annual Growth Rate**
2015	Forecast	74835	1.25
2016	Forecast	91008	1.22
2017	Forecast	108606	1.19
2018	Forecast	127300	1.17
Estimated Average AGR			**1.208**

Table 41: G.IP(ε) = *f*[G.Iu(ε)]

The calculated AGR starting at 1.25 and declining further down to 1.17 seems to be absolutely realistic because:

(i) When compared to the most recent available rate, that of ~1.3 for year 2014, it is very likely to meet the expectation that historical AGRs indicate.

(ii) The progression is smooth and follows the expansion of historical figures.

The expected tendency to prolong a stable trend is demonstrated in the next graph where, apart from a slight deviation in 2012, the overall shape maintains both trends.

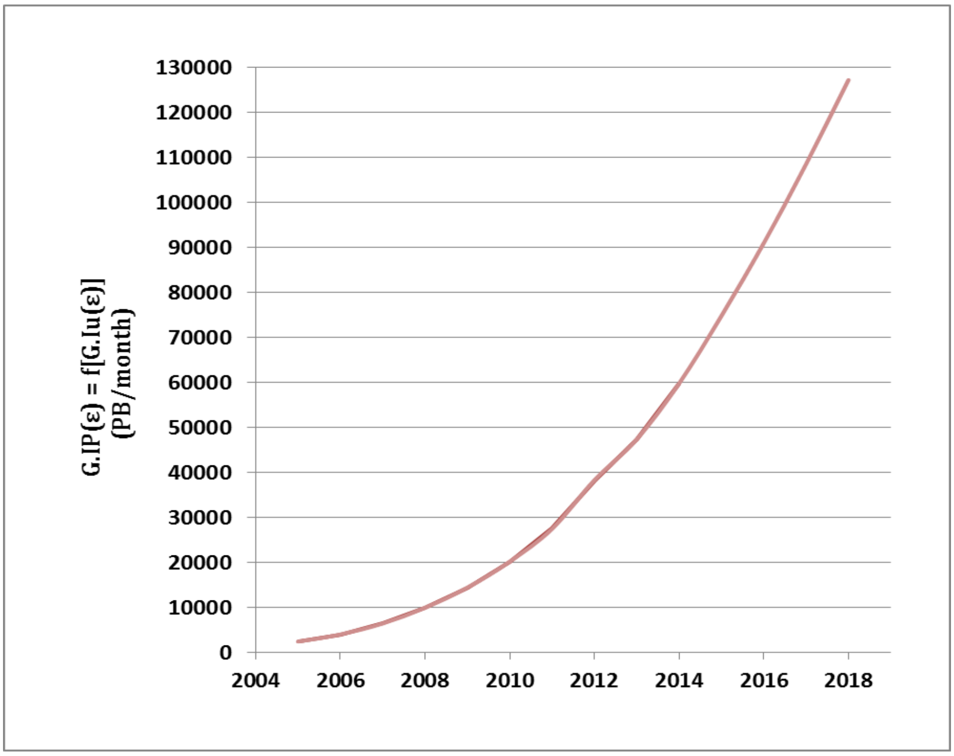


Figure 44: Historical figures (2005-2014) and projections (2015-2018) according to relation (130)

However, forecasts for 2015 according to (130) can be compared with those that have been estimated by the G.IP formulas (45) and (67) for the same year. When referring to tables from relevant chapters, the two latter indicate a total IP traffic at 82918 and 85487 PB per month respectively while equation (130) predicts a more conservative figure at 74835, slightly less than 75 Exabyte (EB) per month. Consequently, their maximum difference is calculated at ~10.6 EB/month between relation (130) and (67), which is not a huge deviation but not small either. Certainly, those equations come from studies that use a variety of parameters and different inputs thus the variation for future figures – although we have no available actual numbers – can be considered reasonable. However, there may be some further explanation regarding the associated timeline:

(i) Studies for the aforementioned produced estimates have a chronological difference of around two years, thus the associated trend may have changed over that time and therefore the more recent version of relation (130) might be more suitable.

(ii) When (67) was proposed and although using it has been proved effective, the formula has a tendency to add more prediction error rate towards 2014 results. If this rate follows a similar increasing tendency, then forecasts for 2015 might significantly deviate from the actual, i.e. more than 10%.

When real IP traffic measurements for 2015 become available, only then we can evaluate if justifications (i) and (ii) are on a reasonable basis or if we are to consider a scenario proposed by forecasts using equation (67).

CHAPTER 9

Some Further Discussion

"Mathematics is the alphabet with which God wrote the Universe"

- Galileo Galilei

This chapter presents some observations and further suggestions as a whole. At the same time it is a concluding part of the thesis with some advice and highlights the importance of ongoing work.

9.1 Exclusion of Important Data

To this point, major historical traffic and users' information have been analysed for modelling and forecasting purposes. The relevant data that have been used satisfy all criteria as described in the methodology chapter and those four conditions should be met in full to produce the most accurate projections. Also, the research that has been conducted hereby covers representative parts of the global activity from large geographical locations that have been or have been not previously put into academic investigation. However, there are significant worldwide data which do not meet this thesis' prerequisites: historical statistics of fixed and mobile traffic on a global level have not been included in the present studies, because their available information reveal certain irregularities which may cause high prediction error rates. The decision that those data have been excluded is mainly based on the following peculiarities:

(i) The presence of a relatively high degree of fluctuations in fixed and mobile traffic.

(ii) The undesired numerical properties that they exhibit as they progress in time.

Table 42 shows the relevant information with the most up to date figures. At a first glance, the numbers of the specimen can be regarded as another suitable set for further investigation and it seems that hidden arithmetical properties do meet all criteria. However, using the same numerical analysis as with all data in previous chapters, certain irregularities have been detected.

Global Internet Traffic in PB per month		
Year	**Fixed Traffic**	**Mobile Traffic**
2005	2055	0.9
2006	3339	4
2007	5219	15
2008	7639	38
2009	10676	92
2010	14929	256
2011	20634	597
2012	31338	885
2013	-	1500
2014	-	2500

Table 42: Fixed and mobile historical Internet traffic [Wik2015a], [Cis2013], [CisVNIb]

Employing equation (20) from chapter 4 and considering that both fixed and mobile historical data can be again represented with an exponential-like relation, we observe the following progression properties illustrated in table 43. As with all proposed formulae (with the exception of relating G.IP with G.Iu of the same year, chapter 8), traffic in a given year is presented and calculated as a function of the previous year. This applies to the global fixed (G.FI) and the mobile (G.MO) parts too, thus their generic form may be given with the following expressions:

$$G.FI(\varepsilon) = [G.FI(\varepsilon-1)]^{P} \tag{133}$$

$$G.MO(\varepsilon) = [G.MO(\varepsilon-1)]^{E} \tag{134}$$

Using similar assumptions, exponents P and E are revealed as time series data with not so consistent properties as the rest of the proposed equations so far.

Numerical Properties of Exponents		
Relating years	**P (eq. 133)**	**E (eq. 134)**
2006 to 2005	1.06363313	N/A
2007 to 2006	1.05504880	1.95344529780
2008 to 2007	1.04450445	1.34324916068
2009 to 2008	1.03743772	1.24307394478
2010 to 2009	1.03614880	1.22632390922
2011 to 2010	1.03367313	1.15269839015
2012 to 2011	1.04206381	1.06158880420
2013 to 2012	-	1.07775785527
2014 to 2013	-	1.06984961435

Table 43: Progression characteristics of global fixed and mobile historical traffic

In table 43, one may observe there is no obvious pattern. There are unstable occurrences of numbers in both exponents, especially as these tend to increase towards later periods instead of following the consistent decline of all years before. In specific, the not so slight increase in 2012 to 2011 of P and the last two undesired fluctuations of the mobile exponent E makes it difficult to decide what methodology should be followed to successfully fit those data and what type of equation would lead to precise future estimations. Furthermore, the rest of the figures of P and E do not have smooth declining properties for all periods 2005-2011 which, again, is another negative aspect to produce a recognized relation for prediction purposes.

As with all investigations so far, most results accommodate a forecasting error of less than 5%, mainly because of the efficiency of the proposed methodology and selection of certain criteria. If the same method had been applied to the inappropriate data of fixed and the mobile global traffic, then a rather higher prediction error (perhaps more than 10%) would probably be more realistic than the successful low rates accomplished with the suitable data sets. Therefore, it may be more appropriate to establish a totally different technique to characterize the fixed and mobile traffic by producing a different prediction equation. For the fixed part, Korotky (2013) [Kor2013] uses regression analysis and proposes a hyperbolic CAGR to project global fixed volumes, as already discussed in the first chapters of this thesis. An attempt to forecast fixed traffic using some other method may not produce accurate results.

9.2 How big should a big or representative Sample of Data be?

The answer to this question cannot be given with precise explanation. In this thesis it has been extensively argued that investigations on long-term modelling and forecasting of Internet traffic volumes and number of users must meet almost in full the proposed criteria as described in chapter three. Those include historical samples over several years of the past and across large geographical areas in order to produce the best fitting results and prediction equations with more than 95% precision, i.e. less than 5% forecasting error. Those levels of error rate have been achieved because of the rigorous selection methodology for the data to be included in the investigation.

Certainly, statistics that come from just a few years from the past cannot be considered as a big sample. Neither can be traffic measurements that have been captured from a small region be treated as representative (e.g. urban zones, big cities, metropolitan areas etc.). On the other hand, samples such as statistics of more than four years and measurements from at least some big countries can be safely used in research as long as the remaining two criteria are satisfied too. In contrast, in a middle situation where there is doubt as to whether the proposed historical information should be investigated, then the answer is probably negative. All samples that are to be considered for high-level research and for valuable contribution to Science must be scrutinized against all four criteria in the first place. Those that meet them in full are highly likely to produce accurate future projections such as with all investigations in this document so far. Similarly, traffic measurements or Internet users' history that exhibit up to medium level fluctuations over time are also positively considered for research but with certain levels of risk in prediction results. Depending on the degree of the fitting success, those are prone to prediction errors at between 5% and 10%, which is still acceptable, but there is no guarantee whatsoever that this rate will not exceed 10%. Fortunately, the latter excessive percentage has not been a result in any part of these studies but, again, it may happen any time in relevant future work even if the chances are rather low.

9.3 Relevance of Proposed Formulae to other Historical Data

An important observation from this long-time research effort in terms of historical data availability is the lack of recorded information in a more regional level and mainly in Internet traffic rather than in users. Although we have statistics about the global aggregate volume of IP, fixed and mobile traffic, we do not seem to possess enough long-term historical evidence of countries or continents. This fact is a limitation to allow us to reveal how certain proposed equations on a global level can be related to smaller samples. For example, it would be useful to compare a proposed formula which projects global IP traffic with another one that predicts the same type of traffic but for a big country and how the format and range of the parameters of those two equations are related to each other.

On the other hand, historical figures from Internet users are not only available for the total global sample but there is information on a smaller scale as well. The top three countries around the world in terms of population – China, India and the United States of America – constantly increase in terms of Internet users according to the latest updates (as of July 2014) and the number of their users are ranked at the top three as well [Ils2015b], [Ils2015c], [Ils2015d]. Similarly and as of November 2015, those countries appear to have more or less the same tendencies, both in terms of population and users and their figures can be seen in [Iws2015b]. Some of their most important statistics are available in the appendix. Internet users in China and India have higher growth rates when compared to those of the United States in the last several years. In the USA, however, the historical numbers of users tend to increase in a similar way with the total worldwide users even though there are some notable differences. The number of users in the USA might soon be reaching a maximum and thereafter only increase at the rate of their population, while in India and China there will be a large proportion of the population who are still not users. While the global figures encompass those of the developing countries where growth rates are faster, the developed parts of the world including Europe and North America have a lower but steadier growth pace and the latter seems to have certain consistencies which are present in the global figures as well. The proposed formula in chapter seven to predict global users for the next three years might be suitable for some regional users' forecasts too, provided it will be used proportionally to the population and/or users and subject to certain changes in its parameters.

Some regression analysis and pattern detection on historical data of China and USA Internet users suggests that an exponential-like equation can be used to predict the number of their users at least two years ahead but for no more than three years, again, due to the uncertainty. Moreover, according to some basic analysis, it was explicitly shown that a potentially proposed relation for those two big countries may probably have the same shape and format with the already proposed formula (84) of chapter seven but with a different numerator in the exponent and a slight change to another variable. It may be also the case that a general prediction equation be proposed at the first stage and, according to the purpose, be then appropriately modified. More specific, equation (84) can be more generally expressed with the following basic format:

$$G.Iu(\varepsilon) = G.Iu(\varepsilon - 1)^{\frac{S1 - \Delta d(\varepsilon - y)}{10000} + S2} \tag{135}$$

Then, from the alternative and rather generic shape of relation (135) a more detailed mathematical version would be accordingly proposed by taking into account the following important aspects:

(i) The significance of number of the investigated Internet users. That is, new proposed equations may fairly vary for big countries when compared to smaller ones.

(ii) The starting values of numerical patterns that are to be calculated at the first stages of pattern detection including the fitting procedure of the historical data. For this, mainly responsible are variables S1 and S2 that crucially define the overall range of the exponent based on the start year of the historical investigation.

(iii) Year y which is the start year for which there are long-term suitable data; this is to propose the timeframe ε–y which is divided into the two usual intervals, the fitting stage and the forecasting period.

(iv) The level of progression of the exponent in time according to pattern detection and regression analysis. A proposed range Δd is to indicate the growth/decline pace of the exponent of which optimum and selected values are to minimize the associated fitting error at that stage.

In addition and in any case, nevertheless, all criteria as already outlined must be also satisfied when proceeding to form equations. The final shape, however, according to each case is an ongoing subject and worth investigating as it will establish a main relation for all levels rather than proposing a different one for each case.

9.4 A Totally different Format of Equations?

The procedure of establishing a forecasting model must be based on personal intelligence and up-to-date facts but at the same time on successful techniques from other researchers as well. In this thesis, the format of most of the proposed formulae has some similarities with those of the University of Minnesota Internet Traffic Studies (MINTS) [UoM1, UoM2], Korotky's regression relation [Kor2013] and the equation proposed by Labovitz et al (2010). The exponential-like shape is common but the assumptions vary according to the selected methodology and circumstances. In my opinion, what makes a forecasting model successful is the accuracy of its predictability evaluated against the actual figures and the option to revise it with a minimum effort as soon as trends change. The selection of the formulae as they have been presented hereby, certainly justify the prediction accuracy but the revision process is still not necessary as the earliest update to any equation here is to take place some time in 2016.

However, one may come up with a considerably different version of suggested relations by choosing to ignore the consistency of the exponential format as it has been proposed over the last several years. As a matter of fact some alternative methodology in the future might suggest an overall linear shape with some level of semi-exponential influence. Moreover, the macroscopic uncertainty of user trends and the constant decline of annual growth rates may introduce a different generation of mathematical models close to linear, since an alternative but realistic scenario is the fact that Internet traffic volume may some time become almost the same year-over-year. At present there is no convincing evidence that this can happen but considering the stable pace of historical AGR decay figures (and the AGRs we expect for the future as investigated), we might witness an era where aggregate yearly volumes could remain stable albeit with a small level of tolerance.

CHAPTER 10

Conclusions and Ongoing Work

"Most people say that it is the intellect which makes a great scientist. They are wrong: it is character"

- Albert Einstein

This final chapter summarizes the proposed prediction scheme and its contribution. Advice is given to address important issues in network planning and for future work with some proposed collaboration from diverse scientific fields.

10.1 Main Conclusions

Characterizing and forecasting Internet traffic volumes on a long-term basis is essential for resources allocation, hardware infrastructure and investment planning. Future projections of Internet users is as well significant as most of the traffic generated across the Internet comes from subscribers' connections. Through these studies, a certain methodology defined by four prerequisite conditions has been proposed to model and forecast Internet traffic and users for the next three years ahead. The investigation uses pattern detection and variables' relations in historical data from several years to make macroscopic estimations. It has been shown that all proposed mathematical relations have excellent fitting characteristics in history traffic and Internet users and have provided very accurate future projections. The predictability of the suggested formulae has in most cases a prediction error rate of less than 5% where pertinent data have become available; those result, so far, seem to be the most accurate in long-term forecasting research. The format and the selection of parameters of the proposed equations can be updated if and when this becomes necessary in the future, using minimum effort. The process of revision, where applicable, is not to take place before the middle of 2016 and in most cases it may begin in 2018-2019 where all formulae will be evaluated against the actual measurements by that time. From current evaluations however, it is expected that results will probably continue on the same successful precision rate provided that trends will not undergo significant changes. The selection of the prediction timeframe for up to a maximum of three or four years has been proved to be the optimum choice. This proposed restriction on forecasting periods is strongly recommended for any relevant work where long horizon traffic or users prediction is the main subject of research.

10.2 Advice and Future Work

10.2.1 Estimations for the very far future

Companies and investment bodies may need to be shown accurate projections of more than four years ahead. In those cases where the potentially selected timeframe is targeted to the very long run, then the negative implications of the extremely long-term traffic uncertainties can be minimized only if we possess a better understanding of user trends and we are to know some non-technical details. Specifically:

(i) If we know how certain technologies will be advancing in the future, e.g. bandwidth to be offered, computer power, mobile devices evolution, storage capacity etc.

(ii) If prices of emerging technologies can be estimated fairly accurate in advance and a proposed plan of their potential future price behavior can be given.

(iii) If we can successfully model human behavior in terms of how people make use of the Internet over long consecutive periods (e.g. to detect any seasonal variations) as well as in the short term (e.g. weekly). This would include socio-economic details such as income, social status, GDP per capita and main reasons for using the Internet.

In general, forecasting Internet traffic and usage may have strong connections with other non-technical fields such as social, psychological and economical aspects. Careful interpretation of historical data from a computer science and mathematical view combined with strong collaboration of diverse disciplines is recommended for optimum results.

10.2.2 Accurate traffic and users' figures

Extreme variations on the same data sets of historical measurements, where those should be almost the same, must be minimized. As described in the literature review, there have been some significant differences in historical figures of global fixed Internet volumes which is not convenient in the sense that research efforts may be based on inaccurate facts and there would be doubt as to which data set should be used. For this reason priority must be given in capturing precise information and at least two independent bodies should collect traffic traces on a real time and continuous basis. For the same location – for example an IXP or a country or even the entire Internet – the traffic monitoring and collection system of the two independent companies may or may not be the same but this should not affect the quality of the recording procedure. At the end and after the processing stage, the data sets must be nearly the same.

On the other hand, the historical information we have on Internet users from at least three sources appear only with minor differences as demonstrated in chapters seven and eight. This small variation would ideally not exist in order to proceed to absolutely effective forecasting models; however the quality of research in this case would not be negatively affected when selecting either data set that is almost the same with each other.

10.2.3 Research on mobile traffic

The number of mobile devices increases quickly in the last decade and so are a variety of mobile applications. The information we have for that type of activity is fairly limited, however mobile connections and technologies are estimated to have a large share in the future according to Cisco Systems. Global aggregate volume traces of mobile Internet traffic are available up to 2014 (table 42, chapter 9). Even though the data have not been a subject for this thesis, further aspects of the mobile traffic part must be investigated and specifically:

(i) If there is a similar exponential (or any other type of) equation to predict the global and more regional evolution of the mobile traffic in the next few years. It is important that base stations and other intermediate equipment can process extreme traffic loads in the future as mobile activities tend to increase fast.

(ii) How mobile traffic is evolving with regards to the sigmoid function. The latter is sometimes used to show a trend that is growing fast at its initial stages but it then tends to smooth and finally reaches saturation at the end.

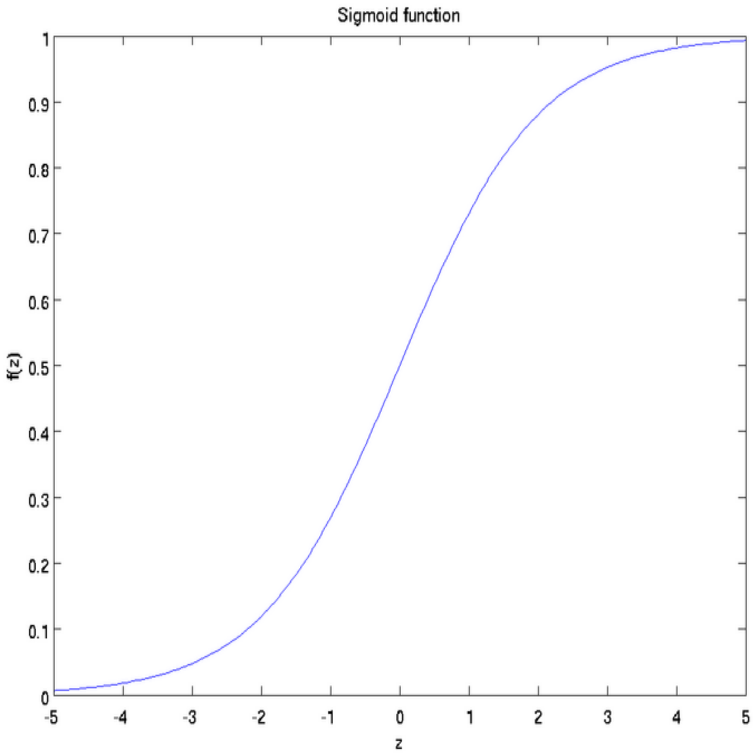


Figure 45: Graphical representation of a sigmoid function [Stan2013]

The growth of the entire global Internet traffic was generally believed to be increasing fast in the 1990s as described in early chapters. At present, nevertheless, it may have reached the smooth part of the shape of figure 45 but the mobile part may yet have not, suggesting that its growth could be located before the smooth side of the sigmoid representation, i.e. at some point in the interval [-5, -1] on the X-axis. If so, research on the behavior of mobile traffic in the future may reveal certain similarities with the entire global IP or fixed type and, in this way, the traffic that is expected for the mobile part after 2015 might be proportionally related to the respective period of the global aggregate volume already investigated. It may sound optimistic, but if some relation could be established between those two important categories then it would be easier to produce further promising mathematical formulae to predict traffic and number of users at geographical areas which, until today, have limited historical information.

10.3 Future Performance of Networks

The increase of Internet traffic in terms of aggregate volumes in most medium and large-scale network infrastructures is inevitable in the next few years and possibly further ahead. As mobile applications and multimedia streaming tend to become the largest parts of traffic categories, there are certain issues that affect networking performance. The quality and delivery of services to customers can be divided into two different types.

10.3.1 Short term performance

The increasing load at networking nodes may be difficult to manage in case of excessive levels of flow. The undesired aspects of real-time traffic such as congestion, rapid accumulation of network queues and some level of information loss can have adverse implications at the levels of IP routing and packet processing. Moreover, this would raise certain questions regarding the security of the network, as it may be exposed to threats from external sources. The overall performance of large networks (Internet service providers, major backbones, Internet exchange points) is highly dependent on their ability to administrate large traffic loads and to what extent. Even high-capacity networks may fail to manage the excessive volumes that must be processed at once and simultaneously for all incoming and outgoing requests. In this way the available network bandwidth becomes saturated reaching its limitations and this practically means users' speed unavoidably decreases. This impact is usually not important in private local networks where the overall bandwidth can be divided by the number of existing customers. But for large geographical providers such as ISPs it is critical to effectively prioritize traffic according to session characteristics e.g. application, destination and level of security.

Information loss and service delays are undesired phenomena in real-time traffic. Future investigation should be effectively focused on these issues and a possible approach would be to prioritize critical applications (e.g. real-time multimedia) and those with increased level of security such as governmental and military connections. Especially for the security-sensitive, it is extremely important to ensure that source and destination are securely established and their connection must be guaranteed in advance.

10.3.2 Long term effect

As opposed to short time scales, the long-time performance of networks is not affected by the bursty properties of real-time Internet traffic. However, the continuously aggregating flow that hundreds of millions of users generate must accord with a considerable level of increase on the overall network capacity not only on ISPs where increasing number of subscribers belong but also at distant peering networks that receive statistically more traffic than other destinations. Installation of appropriate hardware is essential, otherwise this may result in failure of congestion control and severe limitations of the maximum speed rate offered to users.

Another issue is the high demand of cloud computing which is an Internet-based resource of a variety of services and networks with reliable and secure access. Users and companies can benefit from those services and access to these facilities is estimated to increase further. As such, enhanced security and reliable performance of clouds are of utmost importance. Investment and capacity planning of cloud computing resources is also advised as a subject of further investigation to estimate how much traffic is expected to cross certain types of clouds within the proposed future timeframe of three years ahead. It may also be worth investigating the maximum levels of aggregating volumes that the service can process compared to the number of its resources and its maximum bandwidth.

APPENDIX

IP Traffic, 2012–2017	2012	2013	2014	2015	2016	2017	CAGR 2012–2017
By Type (PB per Month)							
Fixed Internet	31,339	39,295	47,987	57,609	68,878	81,818	21%
Managed IP	11,346	14,679	18,107	21,523	24,740	27,668	20%
Mobile data	885	1,578	2,798	4,704	7,437	11,157	66%
By Segment (PB per Month)							
Consumer	35,047	45,023	56,070	68,418	82,683	98,919	23%
Business	8,522	10,530	12,822	15,417	18,372	21,724	21%
By Geography (PB per Month)							
Asia Pacific	13,906	18,121	22,953	28,667	35,417	43,445	26%
North America	14,439	18,788	23,520	28,667	34,457	40,672	23%
Western Europe	7,722	9,072	10,568	12,241	14,323	16,802	17%
Central and Eastern Europe	3,405	4,202	5,167	6,274	7,517	8,844	21%
Latin America	3,397	4,321	5,201	5,975	6,682	7,415	17%
Middle East and Africa	701	1,049	1,483	2,013	2,659	3,465	38%
Total (PB per Month)							
Total IP traffic	43,570	55,553	68,892	83,835	101,055	120,643	23%

Source: Cisco VNI, 2013

IP Traffic, 2013–2018	2013	2014	2015	2016	2017	2018	CAGR 2013–2018
By Type (Petabytes [PB] per Month)							
Fixed Internet	34,952	42,119	50,504	60,540	72,557	86,409	20%
Managed IP	14,736	17,774	20,898	23,738	26,361	29,305	15%
Mobile data	1,480	2,582	4,337	6,981	10,788	15,838	61%
By Segment (PB per Month)							
Consumer	40,905	50,375	61,439	74,361	89,689	107,958	21%
Business	10,263	12,100	14,300	16,899	20,016	23,595	18%
By Geography (PB per Month)							
Asia Pacific	17,950	22,119	26,869	32,383	39,086	47,273	21%
North America	16,607	20,293	24,599	29,377	34,552	40,545	20%
Western Europe	8,396	9,739	11,336	13,443	16,051	19,257	18%
Central and Eastern Europe	3,654	4,416	5,443	6,666	8,332	10,223	23%
Latin America	3,488	4,361	5,318	6,363	7,576	8,931	21%
Middle East and Africa	1,074	1,546	2,174	3,027	4,108	5,324	38%
Total (PB per Month)							
Total IP traffic	51,168	62,476	75,739	91,260	109,705	131,553	21%

Source: Cisco VNI, 2014

Table App. 1: A comparison of two different reports from Cisco's projections on global IP traffic. The lower table comes from [Cis2014a] in June 2014 and appears to be revised when compared to the common period of the upper table which is part of the studies in [Cis2013b] released one year earlier (May 2013).

Year (July 1)	Internet Users**	User Growth	New Users	Country Population	Population Change	Penetration (% of Pop. with Internet)	Country's Share of World Population	Country's Share of World Internet Users	Global Rank
2014*	**641,601,070**	4%	24,021,070	1,393,783,836	0.59%	**46.03%**	19.24%	21.97%	1
2013*	**617,580,000**	10%	53,580,000	1,385,566,537	0.62%	**44.57%**	19.35%	22.77%	1
2012	**564,000,000**	8%	39,887,365	1,377,064,907	0.63%	**40.96%**	19.45%	22.39%	1
2011	**524,112,635**	12%	57,693,872	1,368,440,300	0.63%	**38.30%**	19.55%	22.96%	1
2010	**466,418,762**	19%	75,908,219	1,359,821,465	0.63%	**34.30%**	19.66%	22.80%	1
2009	**390,510,543**	29%	87,052,975	1,351,247,555	0.63%	**28.90%**	19.77%	22.11%	1
2008	**303,457,569**	42%	89,962,607	1,342,732,604	0.63%	**22.60%**	19.88%	19.31%	1
2007	**213,494,961**	53%	73,942,548	1,334,343,509	0.62%	**16.00%**	20.00%	15.55%	2
2006	**139,552,413**	24%	27,200,814	1,326,146,433	0.60%	**10.52%**	20.11%	12.03%	2
2005	**112,351,599**	17%	16,691,349	1,318,176,835	0.59%	**8.52%**	20.24%	10.93%	2
2004	**95,660,250**	18%	14,886,014	1,310,414,386	0.58%	**7.30%**	20.36%	10.51%	2
2003	**80,774,236**	36%	21,245,066	1,302,810,258	0.58%	**6.20%**	20.49%	10.37%	2
2002	**59,529,170**	75%	25,533,367	1,295,322,020	0.58%	**4.60%**	20.62%	8.98%	2
2001	**33,995,803**	50%	11,256,503	1,287,890,449	0.58%	**2.64%**	20.76%	6.79%	3
2000	**22,739,300**	152%	13,724,668	1,280,428,583	0.59%	**1.78%**	20.90%	5.50%	4

Year (July 1)	Internet Users**	User Growth	New Users	Country Population	Population Change	Penetration (% of Pop. with Internet)	Country's Share of World Population	Country's Share of World Internet Users	Global Rank
2014*	**243,198,922**	14%	29,859,598	1,267,401,849	1.22%	**19.19%**	17.50%	8.33%	3
2013*	**213,339,324**	37%	57,763,380	1,252,139,596	1.25%	**17.04%**	17.48%	7.87%	3
2012	**155,575,944**	27%	32,605,503	1,236,686,732	1.27%	**12.58%**	17.47%	6.18%	3
2011	**122,970,441**	36%	32,548,593	1,221,156,319	1.29%	**10.07%**	17.45%	5.39%	3
2010	**90,421,849**	48%	29,486,779	1,205,624,648	1.30%	**7.50%**	17.43%	4.42%	4
2009	**60,935,069**	18%	9,484,859	1,190,138,069	1.32%	**5.12%**	17.41%	3.45%	6
2008	**51,450,210**	12%	5,665,948	1,174,662,334	1.34%	**4.38%**	17.39%	3.27%	6
2007	**45,784,262**	43%	13,709,281	1,159,095,250	1.38%	**3.95%**	17.37%	3.33%	6
2006	**32,074,981**	19%	5,157,948	1,143,289,350	1.43%	**2.81%**	17.34%	2.76%	7
2005	**26,917,033**	23%	4,969,545	1,127,143,548	1.49%	**2.39%**	17.30%	2.62%	7
2004	**21,947,488**	19%	3,500,884	1,110,626,108	1.54%	**1.98%**	17.26%	2.41%	8
2003	**18,446,604**	11%	1,888,210	1,093,786,762	1.59%	**1.69%**	17.20%	2.37%	9
2002	**16,558,394**	137%	9,564,138	1,076,705,723	1.62%	**1.54%**	17.14%	2.50%	8
2001	**6,994,257**	27%	1,495,988	1,059,500,888	1.65%	**0.66%**	17.08%	1.40%	12
2000	**5,498,269**	96%	2,697,680	1,042,261,758	1.68%	**0.53%**	17.01%	1.33%	9

Table App. 2: Historical number of Internet users of the planet's two most populous countries, China [Ils2015b] and India [Ils2015c]. We can observe a large users growth rate over the 15-year timeframe (estimated figures indicated with *).

Year (July 1)	Internet Users**	User Growth	New Users	Country Population	Population Change	Penetration (% of Pop. with Internet)	Country's Share of World Population	Country's Share of World Internet Users	Global Rank
2014*	**279,834,232**	7%	17,754,869	322,583,006	0.79%	**86.75%**	4.45%	9.58%	2
2013*	**262,079,363**	2%	4,820,086	320,050,716	0.80%	**81.89%**	4.47%	9.66%	2
2012	**257,259,277**	5%	12,059,473	317,505,266	0.82%	**81.03%**	4.48%	10.21%	2
2011	**245,199,804**	6%	14,136,938	314,911,752	0.85%	**77.86%**	4.50%	10.74%	2
2010	**231,062,866**	5%	11,323,622	312,247,116	0.89%	**74.00%**	4.51%	11.29%	2
2009	**219,739,244**	-3%	-7,187,049	309,491,893	0.92%	**71.00%**	4.53%	12.44%	2
2008	**226,926,293**	0%	-913,771	306,657,153	0.94%	**74.00%**	4.54%	14.44%	2
2007	**227,840,064**	10%	20,396,520	303,786,752	0.94%	**75.00%**	4.55%	16.59%	1
2006	**207,443,544**	2%	4,786,057	300,942,917	0.93%	**68.93%**	4.56%	17.88%	1
2005	**202,657,487**	6%	11,305,084	298,165,797	0.91%	**67.97%**	4.58%	19.72%	1
2004	**191,352,402**	6%	10,652,029	295,487,267	0.89%	**64.76%**	4.59%	21.03%	1
2003	**180,700,374**	6%	10,063,872	292,883,010	0.90%	**61.70%**	4.61%	23.21%	1
2002	**170,636,502**	21%	29,513,092	290,270,187	0.95%	**58.79%**	4.62%	25.75%	1
2001	**141,123,410**	15%	18,522,528	287,532,638	1.03%	**49.08%**	4.63%	28.19%	1
2000	**122,600,882**	22%	21,715,714	284,594,395	1.13%	**43.08%**	4.64%	29.65%	1

Table App. 3: Internet users in the United States of America [Ils2015d]. Users' growth is significantly lower than in China or India. However, the penetration rate in the USA is consistently higher than the respective rate of the other two countries.

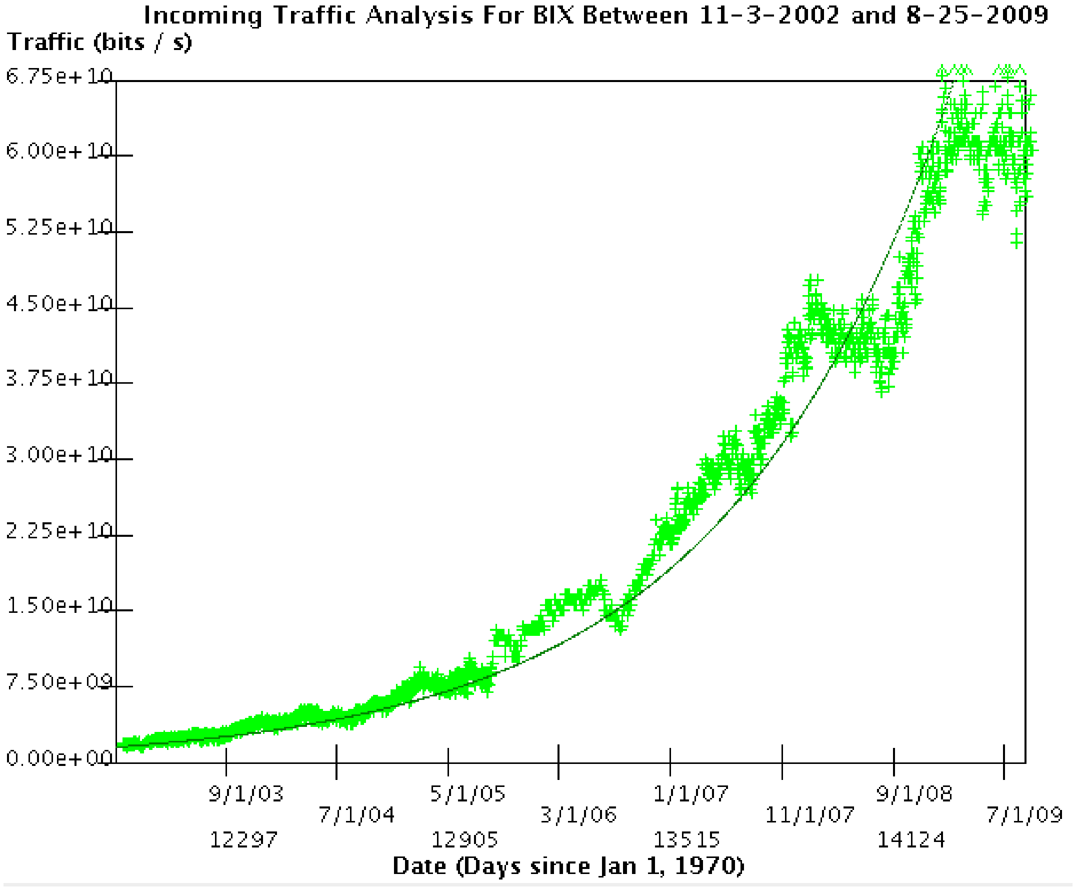


Figure App. 1: Incoming traffic at one of the largest IXP, the Budapest Internet Exchange (BIX) point. Traces are from November 3, 2002 to August 25, 2009 [UoM2]. The curve has good fitting properties over the historical data but there is no reference on the fitting error rate. The incoming mathematical relation is of the form $y = 10^{0.81} * 10^{0.0007x}$ where x is the day.

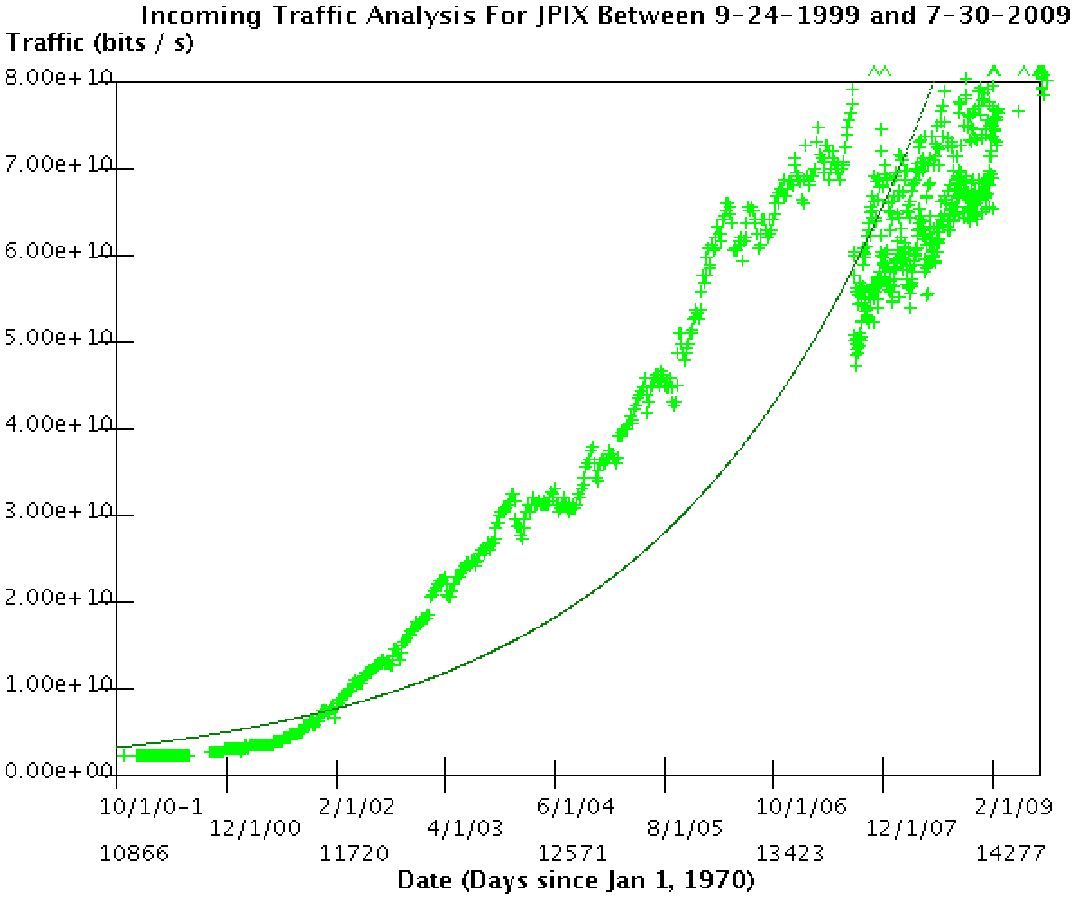


Figure App. 2: Incoming traffic at another large IXP taken from the MINTS: the Japan Internet Exchange (JPIX). The regression curve that fits to the historical traces seems to have some considerable dispersion. The AGR has been calculated at 1.44 and the relation is $y = 10^{4.81} * 10^{0.0004x}$ [UoM2].

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