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Analysis of Prediction Techniques of Key Parameters in IP Networks

Relatore
prof. Antonio Pescapè

Candidato
Salvatore Giuliano
matr. 534/2961

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Introduction

"Why Prediction?"

This work would be a useful contribution to the students and researchers that are interested in making a prediction and forecasting of IP network parameters such as the Bitrate, Delay, Jitter, Packet loss and the Link Load.

Network performance prediction is an active area of research . In the latest studies, attention has been paid to the topic of complex networks, which characterizes many natural and artificial systems such as airline transport systems, power grid infrastructures, Internet and the World Wide Web.

For an Internet Service Provider the analysis of the network traffic through the links of its own network is needed for the critic operations regarding the network's resources.

For example, for an Internet Service Provider the analysis of the network traffic through the links of its own network infrastructure is preparatory to a set of critical operations relating to the management of the network's resources.

To accurately and efficiently manage the resources of its infrastructure, the ISP must know the characteristics of traffic flows through it, in particular : bitrate, delay and Link Load. The knowledge of this last parameter enables a basic capacity planning and resource provisioning activities.

A thorough knowledge of these parameters, thus, allow an optimization of network traffic flows, according to the quality requirements and the specific characteristics of the applications used by network users spread.

Various techniques of prediction are applied for this purpose. These techniques, starting from the time series of the interested network parameter, allow the network to obtain a projection of the behavior that the parameter will take in future instants of time. An accurate prediction of various network parameters reflect as accurately as possible the actual traffic patterns.

Prediction plays a fundamental role in the network's performance improvement. Several works which have been developed in the literature are interested in resolving the problem of improving the efficiency and effectiveness of the network traffic. In fact there are many fields in which a prediction is made to monitor and improve systems and techniques.

A clear and reliable definition of *prediction* in this sense has not yet been formulated. In general, a prediction or forecast is a statement about the way things will happen in the future, often but not always based on experience or knowledge. A prediction may be a statement with an expected outcome, while a forecast may cover a range of possible outcomes.

In order to provide a clear and reliable deal, a wide description of the most widely used techniques is proposed , platforms and tools in the prediction field. All this stuff is supported by a massive comparison and analysis of the most used techniques over the various network technologies. A classification of about an hundred of papers gives a big picture of the *"state of the art"* and gives a point of view on future works and issues.

Next to this part, a chapter was completely dedicated to a description of the most used platforms and toolkits.

After this wide description of the state of the art, a description of the Testbed used for the implementation of the most effective techniques, in reference to some practical scenarios which foresee the analysis of Time series obtained by the WiFi MagNets network in Berlin, from configurations of heterogeneous networks, and from the Slovak academic network SANET. In particular, for the first two cases, the data were extrapolated using the D-ITG software developed by the Department of Computer and Systems Engineering of the University of Naples "Federico II", while the SANET network data were obtained using the software MRGT, Multi Router Traffic Grapher Tool.

At the end of this work there is a discussion about results and future follow-up.

Chapter 2

Introduzione

"Perchè fare prediction?"

Questo lavoro vuole essere un utile contributo per studenti e ricercatori che sono interessati nel fare *prediction* (predizione) e forecasting di parametri caratteristici di rete IP, tra cui il Bitrate, il Delay, il Jitter, il Packet loss ed il Link Load. L'analisi e la prediction di tali parametri fornisce utili informazioni su quali sono i flussi critici e che quindi dovranno essere gestiti con particolare attenzione.

La previsione delle prestazioni di rete rappresenta un'attiva area di ricerca. In recenti studi molta attenzione è stata dedicata alla gestione ed ottimizzazione di reti complesse, che caratterizzano molti sistemi naturali e artificiali, come sistemi di trasporto aereo, le infrastrutture di rete elettrica, Internet ed il World Wide Web.

Per un Internet Service Provider, ad esempio, l'analisi del traffico che transita sui collegamenti (link) della propria rete è propedeutica ad un insieme di operazioni critiche relative alla gestione delle risorse della rete.

L'ISP per gestire in modo più preciso ed efficiente le risorse della sua infrastruttura deve conoscere le caratteristiche dei flussi di traffico che la attraversano, in particolare: il Bitrate, il Delay ed il Link Load. La conoscenza di quest'ultimo parametro, abilita una basilare attività di capacity planning (pianificazione della capacità) e resource provisioning (approvvigionamento delle risorse).

Una conoscenza approfondita di questi parametri, quindi, permetterà una ottimizzazione della gestione dei flussi di rete, tenendo anche conto dei requisiti di qualità e delle caratteristiche specifiche delle applicazioni utilizzate dagli utenti della rete stesa.

È a questo scopo che vengono applicate le varie tecniche di prediction che, partendo da serie storiche del parametro di rete interessato, consentono di ottenere una proiezione del comportamento che il parametro assumerà in futuri istanti di tempo. Un'accurata predizione dei vari parametri di rete riflette nel modo più preciso possibile il reale andamento del traffico.

La previsione gioca quindi un ruolo fondamentale nel miglioramento delle prestazioni di una rete. Analizzando i parametri caratteristici di rete , quali Delay , Packet Loss, Bitrate e Jitter è possibile capire aspetti importanti del flusso di dati che attraversa la rete e quindi agire per garantire una efficienza sempre maggiore.

Diversi documenti in letteratura sono volti a risolvere il problema di migliorare l'efficienza e l'efficacia delle reti monitorandone e predicendone il comportamento, tuttavia una definizione chiara e affidabile del termine *prediction* inteso in questo senso non è stata ancora formulata. In generale, fare "prediction" o "forecasting" consiste nel dare una dichiarazione sul modo in cui le cose accadranno in futuro (più o meno prossimo), spesso ma non sempre, sulla base di *esperienza* o *conoscenza*. La prediction può essere intesa come una dichiarazione di qualcosa di aspettato, mentre il forecasting può coprire una vasta gamma di possibili risultati.

Al fine di fornire un documento chiaro e affidabile, è proposta un'ampia descrizione delle tecniche più diffuse. Le tecniche analizzate sono suddivisibili in due gruppi distinti. Sono descritte tecniche basate su modelli e tecniche basate su apprendimento. Una classificazione di circa un centinaio di documenti, completa il quadro generale dello *"stato dell'arte"*. A seguire, un capitolo è stato interamente dedicato alla descrizione di alcune delle piattaforme e dei toolkit più utilizzati.

Dopo aver dato un'ampia descrizione dello stato dell'arte è descritto il *testbed* utilizzato per l'implementazione delle tecniche più affermate, in riferimento ad alcuni scenari pratici che vedono l'analisi di serie storiche ottenute dalla rete WiFi MagNets di Berlino, da configurazioni di rete eterogenee e dalla rete accademica slovacca SANET. In particolare, per i primi due casi, i dati sono stati estrapolati utilizzando il software D-ITG sviluppato dal Dipartimento di Informatica e Sistemistica dell'Università degli Studi di Napoli "Federico II", mentre i dati relativi alla rete SANET, sono stati ottenuti utilizzando il software MRGT, Multi Router Traffic Grapher Tool.

A conclusione del presente lavoro vi è una discussione sui risultati raggiunti e sui possibili follow-up relativi a questo lavoro.

Chapter 3

Analyzed Techniques : a Brief Review

Here it is a brief review of the most used techniques in prediction fields. After a background on Time-series, in this work, are presented two different approaches to perform traffic prediction. In first place are decrypted some of the most used techniques based on mathematical models (model-based techniques) and then is presented an approach based on learning (learning-based techniques).

3.1 Background on Time-Series

In this section a short but effective background on Time-Series (TS) is given. We refer to a survey on time series developed by Makridakis [127] and to the fundamental text on Time-Series realized by Jenkins [129]. After a formal definition of Time-Series and Time-Series Analysis, there is a glossary on TS [132] adapted to forecast problems, in order to have a quick reference of the terminology which is used.

3.1.1 Time-Series

A time series, $z(t)$, is a set of observations ordered sequentially in time. Khintchine showed that it can be viewed as a sequence of the random variables z_1, z_2, ..., z_n, sampled at equidistant time intervals t_1, t_2, ..., t_n. Each time point can be represented as:

$$z_t = z_t^{'} + u_t \tag{3.1}$$

where $z_t^{'}$ is generated by the real process represented through the time series, and u_t is a white noise term. Usually u_t is expressed with a normal distribution where:

$$E[u_t] = 0 \tag{3.2}$$

and

$$E[u_t u_{t+i}] = \begin{cases} \sigma_u^2 & \text{if } i = 0 \\ 0 & \text{if } i \neq 0 \end{cases} \tag{3.3}$$

A key point is discovering some specifical characteristics of the time series in order to manipulate the data for several applications (in our case we refer to forecasting).

3.1.2 Time-Series Analysis

Time-Series Analysis involves the analysis of data in order to discover their characteristics (stationarity, amplitude, frequency, phase). There are two methods: Autocorrelation Analysis (AA) and Spectral Analysis (SA). The AA uses *autocorrelation function* to analyze data in terms of their time characteristics (e.g. stationarity, seasonality). The SA uses the *spectral function* to discover the frequency characteristics of the process (amplitude, frequency, phase). Moreover, AA enables us to determine if the series is stationary or not, while SA allows us to estimate the gain function of a filter.

Stationarity

A time series is stationary if it has constant mean and variance. The main advantage of dealing with stationary series is that their statistical properties are independent from time and their stochastic characterization is easier. Since in practical problems a large number of actual time series are not stationary, there were developed several methods which allow us to transform a non-stationary series into one which is indeed stationary. A non-stationary time series includes a trend element which can be represented by a function of time:

$$T_t = a + b_1 t + b_2 t^2 + b_3 t^3 + ... \tag{3.4}$$

If we can estimate (3.37) and then subtract it (or divide it into) the time series z_t, the result will be a de-trended series. In such a way we can apply the theory of stochastic process. Estimating T_t in (3.37) a problem may occur, due to the fact that we have to decide on the degree of polynomial to be fitted. Moreover, we have to decide how many terms (observations) we want to use in fitting the polynomial. To do this, we use an approach called "method of moving average" by statisticians and "low-pass filtering" by engineers.

Autocorrelation Analysis

Given the stationary time series (3.1):

$$z_t = z_t^{'} + u_t$$

if we assume that u_t is normally distributed, then z_t can be described by mean, autocovariance and autocorrelation:

$$E[z_t] = \frac{\sum_{t=1}^{n} z_t}{n} = \overline{z} \tag{3.5}$$

$$E[(z_t - \overline{z})^2] = \frac{\sum_{t=1}^{n} (z_t - \overline{z})^2}{n-1} = \sigma^2 \tag{3.6}$$

$$E[(z_t - \overline{z})(z_{t+k} - \overline{z})] = \frac{\sum_{t=1}^{n-k} (z_t - \overline{z})(z_{t+k} - \overline{z})}{n} = \gamma_k \tag{3.7}$$

$$\frac{E[(z_t - \overline{z})(z_{t+k} - \overline{z})]}{E[(z_t - \overline{z})^2]} = \frac{\sum_{t=1}^{n-k} (z_t - \overline{z})(z_{t+k} - \overline{z})}{\sum_{t=1}^{n} (z_t - \overline{z})^2} = \frac{\gamma_k}{\sigma^2} = \rho_k \tag{3.8}$$

If we accept the convention to substitute $z_t - \overline{z} \to z_t$, (3.7) and (3.8) become:

$$\gamma_k = \frac{\sum_{t=1}^{k} z_t z_{t+k}}{n} \tag{3.9}$$

$$\rho_k = \frac{\sum_{t=1}^{n-k} z_t z_{t+k}}{\sum_{t=1}^{n} z_t^2} \tag{3.10}$$

Autocorrelations are measures of relationship between successive values of a variable ordered in time. They vary from -1 to $+1$ and, because of stationarity, are even $\rho_{-k} = \rho_k$. Autocorrelations are used for several purposes. For example they are used to determine the *Existence of Stationarity*. The autocorrelation coefficients of a stationary time series go to zero quickly. If this is not the case, the first difference should be taken and the autocorrelations of the de-trended series found. If they go to zero quickly, it means that the differenced series is stationary. And so on.

Spectral Analysis

If we consider the Fourier transform cosine of the autocorrelation function we obtain the *Spectral Density Function* $S(f)$:

$$S(f) = 2\left(1 + 2\sum_{k=1}^{n-1} \rho_k \cos 2\pi f k\right) \tag{3.11}$$

where the frequency f will always vary from 0 to 0.5, unless otherwise specified.
In a linear system in which $S_i(f)$ is the input spectra, $S_o(f)$ the output spectra and $G(f)$ is the gain function between input and output, we have that:

$$S_o(f) = S_i(f)\,|G(f)|^2 \tag{3.12}$$

3.1.3 Time-Series: A Glossary

Time Series. *A time series is a sequence of observations which are ordered in time (or space). The series value z is plotted on the vertical axis and time t on the horizontal axis. Time is called the independent variable. There are two kinds of time series data:*

- *Continuous, where we have an observation at every instant of time, e.g. electrocardiograms. We denote this using observation z at time t, $z(t)$.*
- *Discrete, where we have an observation at (usually regularly) spaced intervals. We denote this as z_t.*

Trend. *Trend is a long term movement in a time series. It is the underlying direction (an upward or downward tendency) and rate of change in a time series, when allowance has been made for the other components. A simple way of detecting trend in seasonal data is to take averages over a certain period. If these averages change with time we can say that there is evidence of a trend in the series. There are also more formal tests to enable detection of trend in time series.*

Seasonal Component. *In daily, weekly or monthly data, the seasonal component, often referred to as seasonality, is the component of regular fluctuations in a time series which is dependent on a time period. For example, the costs of various types of fruits and vegetables, average daily rainfall and, in computer networks, network traffic intensity during different time of day and night, all show marked seasonal variation.*

Cyclical Component. *In weekly or monthly data, the cyclical component describes any regular fluctuations. It is a non-seasonal component which varies in a recognizable cycle.*

Irregular Component. *The irregular component is that left over when the other components of the series (trend, seasonal and cyclical) have been accounted for.*

Smoothing. *Smoothing techniques are used to reduce irregularities (random fluctuations) in time series data. They provide a clearer view of the true underlying behavior of the series. In some time series, seasonal variation is so strong it obscures any trends or cycles which are very important for the understanding of the process being observed. Smoothing can remove seasonality and makes long term fluctuations in the series stand out more clearly. The most common type of smoothing technique is moving average smoothing. Since the type of seasonality will vary from series to series, so must the type of smoothing.*

Exponential Smoothing. *Exponential smoothing is a smoothing technique used to reduce irregularities (random fluctuations) in time series data, thus providing a clearer view of the true underlying behavior of the series. It also provides an effective means of predicting future values of the time series (forecasting).*

Moving Average Smoothing. *A moving average is a form of average which has been adjusted to allow for seasonal or cyclical components of a time series. Moving average smoothing is a smoothing technique used to make the long term trends of a time series clearer. When a variable, like the number of unemployed, or the cost of strawberries, is graphed against time, there are likely to be considerable seasonal or cyclical components in the variation. These may make it difficult to see the underlying trend. These components can be eliminated by taking a suitable moving average. By reducing random fluctuations, moving average smoothing makes long term trends clearer.*

Differencing. *Differencing is a popular and effective method of removing trend from a time series. This provides a clearer view of the true underlying behavior of the series.*

Autocorrelation. *Autocorrelation is the correlation (relationship) between samples of a time series, such as the value of end-to-end delay or throughput and the same values at a fixed time interval later.*

3.2 Model Based Prediction Methods

3.2.1 Overview

ARIMA model, also known as the Box-Jenkins methodology, is a generalized linear time-series analysis model and has been used to understand network traffic. ARIMA/GARCH combines the linear ARIMA model with conditional variance GARCH (Generalized Auto Regressive Conditional Heteroscedasticity). The differencing operator d in ARIMA can optionally be fractional, giving rise to FARIMA models. The main drawback of these approaches is that they cannot predict far into the future because, by definition, they can only predict the patterns/trends they observe. Generally, time-series methods are used only in short term traffic prediction. For this section we refer to [127], [129] for ARMA, ARIMA, FARIMA and Kalman models, to [131] for Holt-Winters description and to [128] for ARCH models description.

3.2.2 Autoregressive (AR) and Moving Average (MA) Schemes

ARMA Schemes assume that a given value of time series is a weighted linear sum of past values and residual deviations. The following scheme (when v is equal to zero) is an autoregressive scheme.

$$
\begin{aligned}
z_{t+v} &= \sum_{i=1}^{p} \phi_t z_{t-i} + \varepsilon_{t+v} \\
&= \phi_1 z_{t-1} + \phi_2 z_{t-2} + ... + \phi_p z_{t-p} + \varepsilon_{t+v}
\end{aligned}
\tag{3.13}
$$

where ϕ_i represents the autoregressive parameters (or weights) and ε_t is the residual deviation. Let us define a lag operator B as:

$$z_{t-1} = B z_t \tag{3.14}$$

and let $\phi(B)$ be a polynomial in the operator B defined as follows:

$$\phi(B) = (1 - \phi_1 B - ... - \phi_p B^p) \tag{3.15}$$

Then the autoregressive process $AR(p)$ can be represented as:

$$\phi(B) z_t = \varepsilon_t \tag{3.16}$$

Since (3.16) implies:

$$z_t = \frac{1}{\phi(B)} \varepsilon_t = \phi^{-1}(B) \varepsilon_t \tag{3.17}$$

the autoregressive process can be thought of as the output z_t from a linear filter with transfer function $\phi^{-1}(B)$, when the input is ε_t. The following is a moving-average process

$$\begin{aligned} z_t &= \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \\ &= \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \end{aligned} \tag{3.18}$$

where ε_t and ε_{t-j} are the residual error at period t and $t-j$ respectively and j is the moving-average parameter. We can also write the (3.18) in the equivalent form:

$$z_t = (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q)\varepsilon_t \tag{3.19}$$

or

$$z_t = \theta(B)\varepsilon_t \tag{3.20}$$

Hence, the moving average process can be thought of as the output z_t, from a linear filter with transfer function $\theta(B)$, when the input is ε_t.

The following is a mixed autoregressive/moving-average character

$$\begin{aligned} z_t &= \sum_{i=1}^{p} \phi_t z_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \theta_j \varepsilon_{t-j} \\ &= \phi_1 z_{t-1} + \phi_2 z_{t-2} + \ldots + \phi_p z_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \end{aligned} \tag{3.21}$$

that is

$$(1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p) z_t = (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q)\varepsilon_t \tag{3.22}$$

or

$$\phi(B) z_t = \theta(B)\varepsilon_t \tag{3.23}$$

where ϕ_i, θ_j and ε_t are defined as before and $\phi(B)$ and $\theta(B)$ are polynomials of degree p and q, in B. We subsequently refer to this process as an ARMA(p, q) process.

3.2.3 Time-Series Decomposition Methods

Time-Series Decomposition Methods work by either "breaking up" the series into trend, seasonal and remainder components, or by passing varying frequency filters through the data to separate low, medium or high frequencies.

3.2.4 ARIMA models

The Autoregressive Integrated Moving Average model of order (p, d, q), denoted as ARIMA(p, d, q), is an extension to the ARMA(p, q) and it has the form:

$$z_t = \sum_{i=1}^{p+d} \varphi_i z_{t-i} + \sum_{k=1}^{q} \theta_k \varepsilon_{t-k} + \varepsilon_t \tag{3.24}$$

where $\{\varphi_i\}_{i=1}^{p+d}$ and $\{\theta_k\}_{k=1}^{q}$ are respectively the autoregressive and moving average parameters. Here, p stands for the autoregressive order, d for the order of differencing, and q for the moving average order. The innovation (disturbance) variable ε_t is assumed to be an independent and identically distributed normal random variable with mean 0 and variance σ^2. Thus, $E[\varepsilon_t^2|\mathcal{F}_{t-1}] = \sigma^2$ where $\mathcal{F}_{t-1}$ includes all the past information up to an including time $t-1$, i.e., the innovation variance is time independent. As the precedent assumptions, form (3.24) can be expressed as:

$$\varphi(B)\nabla^d z_t = \theta(B)\varepsilon_t \tag{3.25}$$

where $\varphi(B)$ is a polynomial in B and ∇ is a *difference* operator, defined as:

$$(z_t - z_{t-1}) = \nabla z_t \tag{3.26}$$

The ARIMA(p, d, q) is used to model homogeneous nonstationary time series.

In order to build an ARIMA model, it is possible to use the Box-Jenkins methodology, as follows:

1. Through transformations and/or differences variance is stabilized and the series trend and stationarity are eliminated, then a stationary series is obtained.

2. For the obtained stationary series a model is identified and estimated explaining the structure of the time series correlation.

3. Model obtained in item 2 is applied inverse transformations allowing establishing variability, trend, and stationarity for the original series.

4. Estimated model is validated through its residual correlation, when they show correlation it is necessary to estimate the parameters again, that is, to return to item 2. The previous iterative procedure is repeated until there is not any significant correlation between the residuals.

From an engineer's point of view, differencing in ARIMA models act as high-pass filters on the trended data. The nonstationary behavior can be even in terms of variance. The latter can become stationary by transforming the data into a logarithmic scale or a fraction of a power (e.g. square root).

The latter can become stationary by transforming the data into a logarithmic scale or a fraction of a power (e.g., square root). In table 3.1 are exposed some key features of ARIMA models.

ARIMA models key points
Have three parts: the autoregression part (AR) that performs linear combination of previous observed values up to a defined maximum lag (denoted p), the moving average part (MA) that takes in count random error terms plus some linear combination of previous random error terms up to a defined maximum lag (denoted q), and the integration part (I) that takes in count the order of differencing (denoted d) needed to reach the stationarity of the time series. This means taking the differences between successive observations and then analysing these differences instead of the actual observations.
Unlike ARMA models, can handle non-stationary time series;
Can work only in the short and mean range of QoS forecasting periods;
Fitting ARIMA models to time series samples have a computational complexity which is bounded by $O(m3T)$, where T is the length of the time series sample, and $m = max(p, q + 1)$;
Cannot capture the bursty and non linear nature of the Internet traffic, due to the fact that ARIMA models have a constant variance;
Extreme outliers may bias the estimates of the seasonal and trend components of ARIMA model;
Estimation and validation is rather impractical for on-line forecasting systems.

Table 3.1: ARIMA models key points

3.2.5 FARIMA models

The Fractional Autoregressive Integrated Moving Average process FARIMA(p, d, q) with $0 < d < 1/2$ is a stationary process with long-range dependence. It is an extension to ARIMA(p, d, q) and defined as:

$$\varphi(B)\nabla^d z_t = \theta(B)\varepsilon_t \tag{3.27}$$

where the operator ∇^d can be expressed using the binomial expansion:

$$\nabla^d = (1 - B)^d = \sum_{k=0}^{\infty} \binom{d}{k} (-1)^k B^k \tag{3.28}$$

FARIMA model are often used in prediction of long range dependent traffic.

3.2.6 ARCH Models

The ARIMA model with conditionally heteroskedastic disturbances can be given by extending model (3.25) to allow the conditional variance of ε_t to change over time. In addition to $p + d + q$ parameters from the ARIMA model, conditionally heteroskedastic extension of order m introduces additional $m + 1$ parameters. An $ARIMA(p, d, q) - ARCH(m)$ (ARCH stands for AutoRegressive Conditional Heteroskedasticity) model can be expressed as follows:

$$z_t = \sum_{i=1}^{p+d} \varphi_i z_{t-i} + \sum_{k=1}^{q} \theta_k \varepsilon_{t-k} + \varepsilon_t \tag{3.29}$$

where

$$\varepsilon_t = \eta_t \sqrt{h_t} \tag{3.30}$$

$$h_t = \alpha_0 + \sum_{k=1}^{m} \alpha_k \varepsilon_{t-k}^2 \tag{3.31}$$

where η_t is assumed to be an independent and identically distributed normal random variable with zero mean and unit variance. The additional $m + 1$ parameters are $\{\alpha_i\}_{i=0}^{m}$. Note that disturbances ε_t are assumed to be uncorrelated but not independent (higher moments may be correlated) unlike model (3.24), i.e., $E[\varepsilon_t \varepsilon_{t-1}] = 0$ and $E[\varepsilon_t^2 \varepsilon_{t-1}^2] \neq 0$. Under the given assumptions, it follows then that the conditional distribution of ε_t, given the past information up to and including time $t-1$. This is normal with mean 0 and variance h_t (time dependent).

3.2.7 Exponential Smoothing Methods

Exponential Smoothing Methods are special cases of autoregressive AR schemes when $v < -1$. Its weights ϕ_i in (3.13) decrease according to some exponential fashion, thus the name "exponential" is used. Exponential smoothing can be applied to time series data, either to produce smoothed data for presentation, or to make forecasts. When the sequence of observations begins at time $t = 0$, the simplest form of exponential smoothing is given by the formulas:

$$s_1 = z_0; \tag{3.32}$$

$$s_t = \alpha z_{t-1} + (1 - \alpha) s_{t-1}; \tag{3.33}$$

where $t > 1$ and α is the smoothing factor, and $0 < \alpha < 1$. By direct substitution of the defining equation for simple exponential smoothing back into itself we find that:

$$
\begin{aligned}
s_t &= \alpha z_{t-1} + (1-\alpha)s_{t-1} && (3.34)\\
&= \alpha z_{t-1} + \alpha(1-\alpha)z_{t-2} + (1-\alpha)^2 s_{t-2} && (3.35)\\
&= \alpha[z_{t-1} + (1-\alpha)z_{t-2} + (1-\alpha)^2 z_{t-3} + (1-\alpha)^3 z_{t-4} + ...] + (1-\alpha)^{t-1} z_0 && (3.36)
\end{aligned}
$$

namely the weights assigned to previous observations are in general proportional to the terms of the geometric progression $\{1, (1-\alpha), (1-\alpha)^2, (1-\alpha)^3, ...\}$. A geometric progression is the discrete version of an exponential function, so this is where the name for this smoothing method originated. The simple form (3.32) (3.33) of exponential smoothing is also known as an exponentially weighted moving average (EWMA). Technically it can also be classified as an Autoregressive integrated moving average ARIMA$(0, 1, 1)$ model with no constant term.

3.2.8 Holt-Winters Forecasting Model

Holt-Winters methods are often used with seasonal time series. There are two kind of techniques: Additive Holt-Winters for additive seasonal characters and Multiplicative Holt-Winters for multiplicative seasonal characters. Seasonality is additive if the seasonal effect increases with the level of the time series. Seasonality is multiplicative if the seasonal effect is independent from the level of the time series. Holt-Winters model generalizes the exponential smoothing model. Let's consider a phenomenon that has a linear trend. It can be represented by a trend plus an irregular component:

$$z_t = \alpha + \beta t + A_t \qquad t = 1, 2, ..., n \tag{3.37}$$

Coefficients α and β can be found with the least squares method. We can use the model in order to forecast the phenomenon a period forward:

$$\hat{z}_{t+1|t} = \alpha + \beta(t+1) = \alpha + \beta t + \beta \tag{3.38}$$

Generally:

$$\hat{z}_{t+l|t} = \alpha + \beta(t+l) = \alpha + \beta t + l\beta \tag{3.39}$$

The trend at time t is $T_t = \alpha + \beta t$ while $C_t = \beta$ is the level, that is the average level on which the series settles. Then

$$\hat{z}_{t+l|t} = T_t + lC_t \tag{3.40}$$

Parameters T_t and C_t can be written in a recursive form:

$$T_t = T_{t-1} + C_{t-1} \tag{3.41}$$

$$C_t = C_{t-1} \tag{3.42}$$

with initial conditions $T_0 = \alpha$ and $C_0 = \beta$. Previous formulas can be generalized by Holt-Winters formulas:

$$\hat{z}_{t+l|t} = T_t + lC_t \tag{3.43}$$

where:

$$C_t = \alpha z_t + (1-\alpha)(C_{t-1} + T_{t-1}) \tag{3.44}$$

$$T_t = \alpha(C_t - C_{t-1}) + (1-\beta)T_{t-1}. \tag{3.45}$$

We can obtain α and β by minimizing the sum of the squares of forecast errors:

$$S(\alpha,\beta) = \sum_{t=2}^{n}(z_t - \hat{z}_{t|t-1})^2 \qquad t = 1, 2, ..., n \tag{3.46}$$

Let consider a time series with a seasonal component S_t with period s.

$$\hat{z}_{t+l|t} = C_t + lT_t + S_{t+l-s} \qquad l = 1, 2, ..., s \tag{3.47}$$

Previous formulas are referred to additive seasonality (amplitude of seasonal effects is constant in time series). When the effects of seasonality increase with time, we're in presence of the multiplicative seasonality. Formulas are:

$$C_t = \alpha\frac{z_t}{S_{t-s}} + (1-\alpha)(C_{t-1} + T_{t-1}) \tag{3.48}$$

$$T_t = \beta(C_t - C_{t-1}) + (1-\gamma)S_{t-s} \tag{3.49}$$

and the prediction of l periods forward at time n is:

$$\hat{z}_{t+l|t} = (C_t + lT_t)S_{t+l-s} \qquad l = 1, 2, ..., s \tag{3.50}$$

In table 3.2 are shown some key points of Holt-Winters forecasting methods.

3.3 Learning Based Method : Artificial Neural Networks

The ultimate goal of Artificial Neural Networks (ANNs) is to realize the learning mechanisms of the human brain, making sure that the network interacts with the external environment without human intervention, as well as that of creation. ANNs can be eyed as generalizations of mathematical models of biological nervous systems. They are usually used to model complex i/o relationships or to find patterns in data. In [86] Hecht-Nielse provide a formal definition of ANN .

Holt-Winters models key points
Often used with seasonal time series;
The forecast is obtained as a weighted average of past observed values where the weights decline exponentially so that the values of recent observations contribute to the forecast more than the values of earlier observations;
Two kinds of techniques: Additive Holt-Winters for additive seasonal characters and Multiplicative Holt-Winters for multiplicative seasonal characters;
Simple exponential smoothing doesn't have good performance when there is a trend in the data, Holt-Winters methods does;
Holt-Winters techniques are sensitive to unusual events or outliers;

Table 3.2: Holt-Winters models in key points

DEFINITION: *A neural network is a parallel, distributed information processing structure consisting of processing elements (which can possess a local memory and can carry out localized information processing operations)interconnected together with unidirectional signal channels called connections. Each processing element has a single output connection which branches("fans out") into as many collateral connections as desired (each carrying the same signal - the processing element output signal). The processing element output signal can be of any mathematical type desired. All of the processing that goes on within each processing element must be completely local: i.e., it must depend only upon the current values of the input signals arriving at the processing element via impinging connections and upon values stored in the processing element's local memory.*

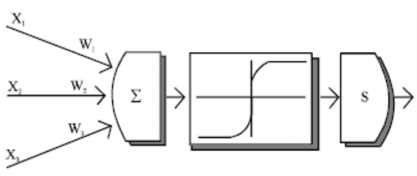


Figure 3.1: Example of artificial neuron with three inputs

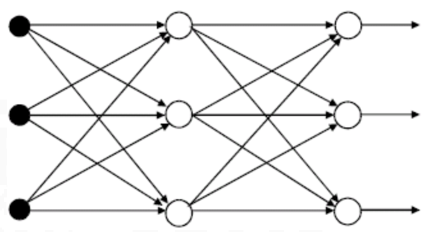


Figure 3.2: Multilayer perceptron architecture

3.3.1 Computational Models of Neurons

Simple neuron (Figure 3.1) introduced by McCulloch and Pitts in 1940s [87], consists of input layer, activation function, and output layer. Input layer receive input signal from external environment (or other neuron). Activation function is the neuron internal states that calculates and sum the input signals. The signals are then transmitted to output layer. The input layer, activation function and output layer in artificial neuron are similar to the function of dendrites, soma and axon in biological neuron.

The computational model of neurons is given from the following equation:

$$S = f\left(\sum_{j=1}^{n} w_j x_j\right),$$

where x_j is the actual input and w_j the input weight. The function f is the transfer (or activation) function . The default transfer functions is the *sigmoid* , but they may also take the form of other non-linear functions, piecewise linear functions or step functions(Figure 3.3). Generally, transfer functions are monotonically increasing.

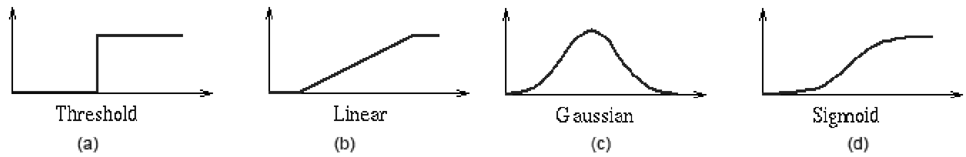


Figure 3.3: Different types of activation functions: (a) threshold, (b) piecewise linear, (c) Gaussian , and (d) sigmoid.

3.3.2 Artificial Neural Networks : A Taxonomy

Based on the connection pattern (architecture), ANNs can be grouped into two categories ([88] Jain and Mao, 1996) (Fig. 3.4):

- Feedforward networks, in which graphs have no loops
- Recurrent (or feedback) networks, in which loops occur because of feedback connections.

In the most common family of *feedforward* networks, called *multilayer perceptron*(MLP), neurons are organized into layers that have unidirectional connections between them (Fig. 3.2).

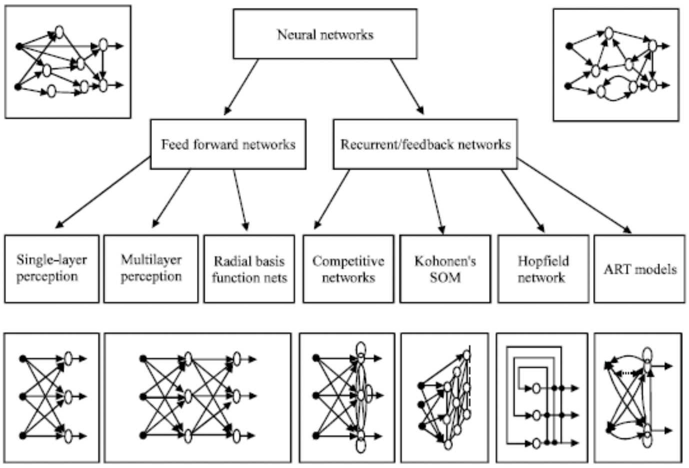


Figure 3.4: Taxonomy of feedforward and feedback network architectures

3.3.3 The Learning Mechanism

The ability to learn is a fundamental trait of intelligence. Although a precise definition of learning is difficult to formulate, a learning process in the ANN context can be viewed as the problem of updating network architecture and connection weights so that a network can efficiently perform a specific task. The network usually must learn the connection weights from available training patterns. Performance is improved over time by iteratively updating the weights in the network.

A learning algorithm refers to a procedure in which learning rules are used for adjusting the weights.

There are two main learning paradigms: **supervised** and **unsupervised**. In *supervised learning*, or learning with a teacher, the network is provided with a correct answer (output) for every input pattern. Weights are determined to allow the network to produce answers as close as possible to the known correct answers. *Reinforcement learning* is a variant of supervised learning in which the network is provided with only a critic on the correctness of network outputs, not the correct answers themselves. In contrast, *unsupervised learning*, or learning without a teacher, does not require a correct answer associated with each input pattern in the training data set. It explores the underlying structure in the data, or correlations between patterns in the data and organizes patterns into categories from these correlations.

Each learning algorithm is designed for training a specific architecture. Therefore, when we discuss a learning algorithm, a particular network architecture association is implied. Each algorithm can perform only a few tasks well ([88]Jain and Mao, 1996) (Fig. 3.5).

Paradigm	Learning rule	Architecture	Learning algorithm	Task
Supervised	Errot-correction	Single or Multilayer perception	Perception Learning Algorithms Back-propagation, Madaline	Pattern Classification, Functions Approximation, Predicition, Control
	Boltzmann	Recurrent	Boltzmann Learning Algorithm	Pattern Classification
	Hebbian	Multilayer Feed-Forward	Linear Diuscriminant Analysis	Data analysis, Pattern Classification
	Competitive	Competitive	Learning Vector Quantization	Within-class Categorization Data Compression
		ART	ARTMap	Pattern Classification Within-class Categorization
Unsupervised	Error-correction	Multilayer Feed-Forward	Sammon's Projection	Data analysis
	Hebbian	Feed-Forward or competitive	Principal component analysis	Data analysis Data compression
		Hopfield Network	Associative memory learning	Associative memory
	Competitive	Competitive	Vector Quantization	Categorization Data compression
	Cohonen's sum	Kohonen's SOM	Kohonen's SOM	Categorization Data analysis

Figure 3.5: Learning paradigms and algorithms

3.3.4 Artificial Neural Network : Training

Training the network is time consuming. It usually learns after several epochs, depending on how large the network is. We could also stop the training after the network meets certain stopping criteria as minimum gradient magnitude, maximum training time , minimum performance value etc.

The best training procedure is to compile a wide range of examples which exhibit all the different characteristics of the problem. To obtain a robust and reliable network it is needed to add some noise to the training data to get the network familiarized with noise and natural variability in real data.

How many neurons?

Selection of the number of hidden neurons is a crucial decision. The number of hidden neurons affects how well the network is able to separate the data. A large number of hidden neurons will ensure correct learning, and the network is able to correctly predict the data it has been trained on,but its performance on new data, its ability to generalize, is compromised. With too few hidden neurons, the network may be unable to learn the relationships amongst the data and the error will fail to fall below an acceptable level. It is evident that we must find the right compromise during the selection of hidden neurons number

About Initial Weights and Learning Rate

There are no recommended rules for the initial weights selection except trying several different starting weight values to see if the network results are improved. The *learning rate* is a value that controls the size of the adjustments made during the training process. If the learning rate is too high, then the algorithm learns quickly but we have oscillations during the training process, if it is lower then the predictions jump around less, but the algorithm takes a lot longer to learn.

3.3.5 (Focused)Time-Delay Neural Networks

Time-Delay Neural Networks (`TDNN`) consist in a *feedforward* network with a *tapped delay line* at the input. It is similar to a multilayer perceptron in that all connections feed forward (Figure 3.6). In the TDNN, the inputs to any node can consist of the outputs of earlier nodes during some numbers of previous time steps. This is generally implemented using tap-delay lines.

A natural restriction of the general TDNN topology is the class of TDNN architectures which have delays *only on the input units* known as **Focused** Time-Delay Neural Network (FTDNN)[133].

Still in [133], the authors make a characterization and contrast the capabilities of the general class of time-delay neural networks(TDNN's) with input delayed neural networks(FTDNN's), the subclass of TDNN's with delays limited to the inputs, that they call IDNN's.

FTDNN can be viewed as the most straightforward dynamic networks.

In Figure 3.6 is shown a time-delay neural network architecture that is equivalent to a single hidden layer feedforward neural network. This network maps a finite time sequence (3.51) in a single output y that is given from the equation 3.52.

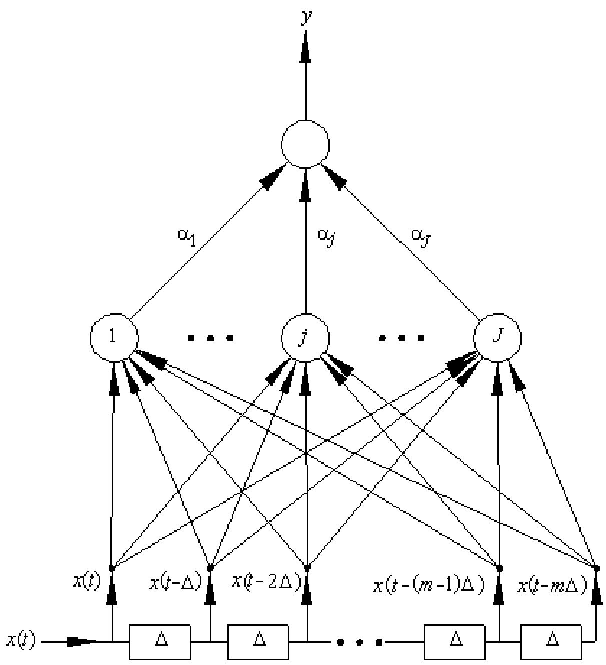


Figure 3.6: A time-delay neural network.

$$\{x(t), x(t-\Delta), x(t-2\Delta), .., x(t-m\Delta)\} \tag{3.51}$$

$$y = \sum_{j=1}^{J} \alpha_j f\left(\sum_{i=1}^{m+1} w_{ji} x(t-(i-1)\Delta)\right) \tag{3.52}$$

where f is the activation of hidden units and Δ is the Delay associated to the input layer.

3.3.6 Recurrent Neural Networks

Recurrent Neural Networks(RNNs) are `the state of the art` in nonlinear time series prediction, system identification, and temporal pattern classification. Contrary to feedforward networks, recurrent neural networks can be sensitive, and be adapted to past inputs. Recurrent neural networks are complex parametric dynamic systems that can exhibit a wide range of different behavior.

Simple recurrent networks (`SRNs`) comprise a class of recurrent neural models that are essentially feedforward in the signal-flow structure, but also contain a small number of local and/or global feedback loops in their architectures. A state layer is updated not only with the external input of the network but also with activation from the previous forward propagation. The feedback is modified by a set of weights as to enable automatic adaptation through learning.

Some popular recurrent network architectures are the `Elman` recurrent network [89] in which the hidden unit activation values are fed back to an extra set of input units and the `Jordan` recurrent network in which output values are fed back into hidden units.

3.3.7 NARX Neural Networks

The last mentioned recurrent architectures are usually trained by means of temporal gradient-based variants of the backpropagation algorithm. However, learning to perform tasks in which the temporal dependencies present in the input/output signals span long time intervals can be quite difficult using gradient-based learning algorithms. In [90], the authors report that learning such long-term temporal dependencies with gradient-descent techniques is more effective in a class of SRN model called **Nonlinear Autoregressive with eXogenous input (`NARX`)** [91] than in simple MLP-based recurrent models.

Despite the aforementioned advantages of the NARX network, its feasibility as a nonlinear tool for univariate time series modeling and prediction has not been fully explored yet.
Potential fields of application of our approach are communication network traffic characterization [92][93] and chaotic time series prediction [94], since it has been shown that these kinds of data present long-range dependence due to their self-similar nature.

This kind of network can be used as a tool for nonlinear system identification with excellent results. In [125] is proposed a way to solve efficiently the issue of nonlinear time series prediction with the NARX network. They propose a simple strategy to allow the computational resources of the NARX network to be fully explored in nonlinear time series prediction tasks.

The Nonlinear Autoregressive model with Exogenous inputs (NARX) [95] is an important class of discrete-time nonlinear systems that can be mathematically represented as :

$$y(n+1) = f[y(n), ..., y(n-d_y+1); \quad u(n), u(n-1), ..., u(n-d_u+1)]; \quad (3.53)$$

where $u(n) \in R$ and $y(n) \in R$ denote, respectively, the input and output of the model at discrete time step n , while $d_u \geq 1$ and $d_y \geq 1$, $d_u \geq d_y$, are the input-memory and output-memory orders.

that may be written as :

$$y(n+1) = f[y(n); u(n)]; \quad (3.54)$$

where the vectors $y(n)$ and $u(n)$ denote the output and input regressors, respectively.

The nonlinear mapping $f(\cdot)$ is generally unknown and can be approximated, for example, by a standard multilayer Perceptron (MLP) network. The resulting architecture is then called a NARX network [96][97].

NARX training

As we can see in [125], there are two configurations for the NARX networks:

- **Series-Parallel (SP) Mode** - In this case, the output's regressor is formed only by actual values of the system's output:

$$\hat{y}(n+1) = \hat{f}[y_{sp}(n); u(n)], \quad (3.55)$$

$$\hat{y}(n+1) = \hat{f}[y(n), ..., y(n-d_y+1); u(n), u(n-1), ..., u(n-d_u+1)]; \quad (3.56)$$

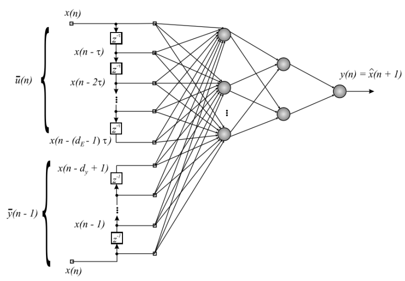


Figure 3.7: NARX : Series-Parallel (SP) Mode

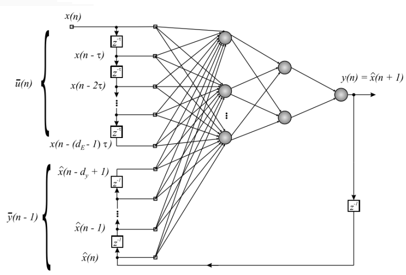


Figure 3.8: NARX : Parallel (P) Mode

- **Parallel (P) Mode** - In this case, estimated outputs are fed back and included in the output's regressor:

$$\hat{y}(n+1) = \hat{f}[y_p(n); u(n)], \tag{3.57}$$

$$\hat{y}(n+1) = \hat{f}[\hat{y}(n), ..., \hat{y}(n-d_y+1); u(n), u(n-1), ..., u(n-d_u+1)]; \tag{3.58}$$

In order to perform a good training the Series-Parallel configuration (open loop) is the right choice, while the Parallel configuration (closed loop) is useful for testing and multi-step-ahead prediction. In table 3.3 there is a short summary of ANN characteristics, while in table 3.4 there is a taxonomy referred to all techniques reviewed in this work.

PRO	CONS
Able to easily handle a great amount of information	Can require considerable parameter tweaking and retraining to fit well
Good behavior with noisy signals	Training is time consuming
Able to generalize the expert knowledge	Can suffer from "interference" in that new data can cause ANN to forget some of what it learned on old data
Can be trained directly on data with thousands of inputs	Training is computationally expansive
Fast prediction speed	Hard to see how input variables affect the responses (BLACK BOX)

Table 3.3: Pros and Cons of Artificial Neural Networks

Table 3.4: Classification of Techniques reviewed according to techniques previously explained.

Techniques	References
AR(MA)	[67, 49, 55, 72, 20, 71, 8, 56, 1]
ARIMA	[31, 36, 8, 66, 54, 60, 12, 41, 21, 17, 53, 72, 62]
Holt-Winters	[36, 30, 70, 5, 49]
Neural Networks	[11, 52, 47, 43, 18, 6, 33, 36, 70, 5, 46, 28, 8, 66, 60, 58, 64, 10]
	[74, 35, 34, 76, 15, 48, 65, 9]
Hybrid Models	[8, 27, 9, 40]

Chapter 4

Network Traffic Prediction : A Big Picture

4.1 Main Key Network Parameters Prediction

4.1.1 Throughput and Network Traffic Prediction

Throughput can be defined as the average rate of a successful packet delivery over a communication channel in a network. Spectral Efficiency refers to the information rate that can be transmitted over a given bandwidth and is measured in $\frac{bit/s}{Herz}$. Since in the first communication systems the spectral efficiency was equal to one, still today the terms bandwidth and throughput are often used interchangeably. Obviously, when we're talking about throughput prediction on an Internet network, we have to specify which transport protocol we refer to, TCP or UDP. Throughput prediction has several applications: by improving this task, for example, network providers can optimize network resources, offering the possibility to ensure a better quality of service. Also, traffic forecasting can help to detect anomalies as security attacks or viruses by comparing the real traffic with the forecasts, as explained in [23].
From the several approaches to throughput prediction we can cite formula-based approaches and history-based approaches [49]. The first predicts throughput using mathematical expressions that involve, in the case of TCP transport protocol, sender's behavior to path and end-host properties (RTT, packet loss rate, receive window size). All these data are plugged into a formula to generate the predicted values. The latter is generally more accurate and typically use some kind of standard time series forecasting based

on throughput measurements and derived from prior file transfers. One of biggest problems with network throughput prediction is that the probability distribution of traffic is unclear and the scale and bandwidth of networks are constantly changing. Moreover, network throughput is much more difficult to predict than end-to-end delay, since throughput has a strongly nonlinear behavior (see [1]).

The conception of throughput prediction is different from the concept of traffic prediction. Essentially because, in the case of throughput, the rate at which packets are transmitted on the network is known. From time series modeling point of view, Holt-Winters (See section 3.2.8) methods were developed for series with trended and seasonal factors, model such as ARMA (see Section 3.2.2), ARIMA (see Section 3.2.4)and Fractional-ARIMA (see Section 3.2.5) are not able to take in count the non-linear behavior of Internet traffic, though ARIMA can capture the nonstationary behavior of traffic . Moreover, network traffic is self similar in nature (self-similarity is the property of a series of data points to retain a pattern or appearance regardless of the level of granularity used), showing high burstiness in a wide range of time scales and obey in the heavy-tail distribution. In the case of TCP flows (TCP is the dominant transport protocol of the network such Internet), congestion window, presence of acknowledgements, multiplexing of packets at bottleneck rate contribute to the propagation of the self-similarity nature of the traffic. From this point of view all these models have a constant variance, and thus cannot capture the real bursty nature of the Internet traffic. This aspect can be solved using ARCH models (see Section 3.2.6) and its variants or with Gegenbauer ARMA (GARMA) models, as written in [44]. Another solution can be using Artificial Neural Network (ANN) Approaches (see Section 3.3) that are capable of predicting self-similar traffic. Information like throughput are used also for bandwidth provisioning, like in [19].

Also SVR method demostrated some useful aspects in throughput prediction: it can accept multiple inputs (i.e., multivariate features) and will use all of these to generate the throughput prediction. Moreover SVR does not commit to any particular parametric form, unlike formula-based approaches. Instead, SVR models are flexible based on their use of so-called nonlinear kernels. This expressive power is the reason why SVR has potential to be more accurate than prior methods. Finally, SVR is computationally efficient, which makes it attractive for inclusion in a tool that can be deployed and used in a wide area.

Specifically, in [31] Anand et al. developed a non-linear time series model, expanding the concept of ARCH with GARCH model (Generalized AutoRegressive Conditional Heteroskedasticity), with innovation process generalized to the class of heavy-tailed distributions. Results showed that GARCH prediction performance are significantly better if compared with ARIMA, ARCH, ARIMA-ARCH models. In [21] ARIMA models are compared with ANFIS models in WiMax network.

Another method examined in literature is SVR. In [67] Rossi et al.explore the use of Support Vector Regression models for the purpose of link load forecast, comparing the performance with Moving Average (MA) and Auto-Regressive (AR) models. Results showed that, despite a not powerful gain for prediction at short time scales, SVR methods are still robust to parameter variations, are scalable and they lead to a significantly extend of the forecast horizon. Another paper [13] compare CDF predictor performance with SVR predictor one demonstrating that its prediction accuracy is higher. And in [3], Mirza et al. made SVR prediction and investigated the relationship between TCP throughput and measurements of path properties including available bandwidth, queuing delays and packet loss.

From the point of view of neural networks, [33] focused the neural network based on multi-layer perceptron (MLP) and trained by Levenberg- Marquardt (LM) and the Resilient back propagation (Rp) algorithms, while in [64], [10] Li et al. focused on a network traffic forecasting strategy based on BP neural network (BP-NTF). In [36] Cortez et al proposed a comparative study between Holt-Winters, the ARIMA methodology and a Neural Network Ensemble (NNE) approach. In particular, the latter produces the lowest error, in both realtime and short-term traffic analysis. Similar comparison was made by Feng et al. in [66], analyzing ARIMA, FARIMA (see also [72]), ANN and Wavelet predictors and comparing their performance with MSE, NMSE. Results showed significant advantages for the ANN technique. Even from ANN related studies, Junsong et al. in [60] compared the Elman Neural Network prediction performance with the one obtained with ARIMA, FARIMA, ANN and Wavelet predictors, obtaining significantly lower prediction errors (MSE and NMSE).

Other studies [46], [45], [69], proposed tools to forecast network traffic. In particular, Eswardass et al. in [46] proposed an improvement on Network Weather Service based on Artificial Neural Network, ensuring better performances in terms of accuracy.

In [59] Goya et al. proposed a method to derive analytic models that predict the throughput of TCP flows between two nodes using network characteristics such as loss and delay and modifying the Amherst model.

4.1.2 Predicting End-to-End Delay

The delay of a network it's a measure of the time needed for a bit of data to travel across the network from one node to another. There are two kinds

Table 4.1: Throughput Forecast Approaches

Techniques and variants	Section	References
AR(MA)	Section 3.2.2	[20]
Neural Networks	Section 3.3	[46],[3]

of delays: Hop-by-Hop delay and End-to-End delay. End-to-end delay is the sum of delays experienced at each hop, from the source to the destination.
There are requirements on end-to-end delay for many Internet real-time applications, such video-conferencing, VoIP, streaming applications and distributed games. Moreover, delay-based approach is used to predict network congestion, to design network protocols and flow control algorithms and to make analytical studies of network configurations. The end-to-end delay may be considered as the sum of two principal components: a constant component which includes the propagation delay and transmission delay and a variable component which includes the processing and queuing delay. The last component is the major source of uncertainty. Parameters that are often used in this field to understand the Internet dynamics are Round Trip Time (RTT), that needs measurements only at one end, and One-way Transmission Time (OTT), that requires the involvement of the receiver to obtain the measure. In [98] and [79] is shown that the mean OTT can't be approximated with half RTT.
For time series data that are stationary, it is possible to use ARMA model (see Section 3.2.2) but most time series data of Internet end-to-end delay are non-stationary so other models like ARIMA models (see Section 3.2.4) are needed. For example [24] proposed a method based on Maximum Entropy Principle (MEP) instead of ARMA model, obtaining better performance, since sometimes delays develop with quick variation. In another work Miloucheva et al. [12] combined ARIMA prediction and outlier detection for short-term and medium-term forecasting, using end-to-end delay QoS measured data. Results showed also that outliers could corrupt the forecasting values for the delay. On the practical point of view, end-to-end delay of a TCP flow is a noisy, nonstationary and nonlinear process, but if the traffic intensity is low, we can observe a stationary behavior. This is very useful for long-horizon end-to-end delay forecasting. In fact, results from [40] showed that on long-horizon end-to-end delay forecasts, an hybrid approach based on discrete wavelet transform, neural network and the k-nearest neighbors techniques performs better than [34] for longer forecasts an performs worse for shorter forecasts (around 64 steps ahead). Recently literature started to analyze the question of end-to-end delay forecasting jointly with other parameters like

Table 4.2: Traffic Forecast Approaches

Techniques and variants	Section	References
AR(MA)	Section 3.2.2	[44], [49],[67]
Holt-Winters	Section 3.2.8	[49], [36],[70]
ARIMA	Section 3.2.4	[21],[36], [41],[60],[66],[72]
Neural Networks	Section 3.3	[9],[10],[11],[23],[30],[33], [36],[48],[60],[65],[66],[76],[64]
ARCH	Section 3.2.6	[19],[31]

Table 4.3: End-to-End Delay Forecast Approach

Techniques	Section	References
AR(MA)	Section 3.2.2	[56],[54],[1],[20]
ARIMA	Section 3.2.4	[12]
Neural Networks	Section 3.3	[40],[34],[43]

throughput, in order to use the possible statistical dependence with end-to-end delay. In fact, Mendoza et al. in [1] made a comparison between AR, SVM (individual version and joint version including information about throughput) and Kalman techniques that showed SVMs models are the best predictor for individual or joint versions. Worse performances are with AR predictor. Problems of delay boundary prediction were studied in [37], and [24].

AR,MA or ARMA [56],[54],[1],[20], ARIMA [12], SVM [1], Neural Networks [40],[34],[43] and their variants, are used to forecast end-to-end delay time series. Other studies [25],[32] involve Hidden Markov Model (HMM) in order to model delay behavior. Multiple Model (MM) proposed in [55] uses a set of models that is assumed to describe the system dynamics through a bank of filters that runs in parallel at the same time and provides a non-stationary and non linear solution for delay prediction. Experimental results shows this technique works better than Least Mean Square (LMS) and Recursive Least Square (RLS), two most widely used linear adaptive filters. Studies on the Internet delay dynamics [34] showed the success of dynamic neural networks as semi-parametric approximators for modeling complex systems involved in this type of phenomena, but it remains an open problem applying neural network method to forecast delay online [43].

4.1.3 Packet Loss Prediction

Packet Loss prediction has gained much interest in last years for many reasons. Monitoring and forecasting packet loss behavior is very quick way to track congestion conditions of a network. In fact, if congestion occurs on a link carrying TCP as well as UDP traffic, TCP will react by reducing the traffic rate, while UDP will not. The rate adjustment is based on packet-loss rate and the round-trip time (RTT). Rather than using previously measured values of packet loss and RTT (a causal effect of RTT on packet loss rate is also demonstrated), a better approach is to use predictions of these quantities. Such a predictive approach will be quicker to track congestion conditions than the typically used reactive approach. Moreover, increasing applications

Table 4.4: Packet Loss Forecast Approaches

Techniques and variants	Section	References
Neural Networks	Section 3.3	[51],[102],[103]
Other methods		[104],[101],[99],[100], [57]

in transmitting audio and video services over IP networks require mechanisms to prevent situation that can determine the degradation of video and audio real time quality, as packet loss situations do. Studies on packet loss prediction are also useful in the wireless sensor networks, in indoor and outdoor environment, since they offer the capability of determining the number of motes, sampling rate and the operational environment to obtain a reliable data transfer for a given sensing application. Packet loss is strongly influenced by Throughput (see [53]) and Long-range Dependent (LRD) Network Traffic. In fact, several studies showed the greater the LRD, the lower the Quality of Service. Nevertheless, in literature there are not so many works on Packet Loss Prediction. Su et al. [99] derived the packet loss probability, conditioned on past loss rates, assuming the Gilbert model, which is a simple two-state Markov model. Salvo Rossi et al. [100] modeled end-to-end packet loss rate for UDP traffic using a hidden Markov model. Roychouduri and Al-Shaer [101] developed an empirically determined formula that predicts end-to-end packet loss rate as a function of available bandwidth, delay variation, and trend. In [102] and [103] Yoo et al. considered a time-series prediction approach for predicting end-to-end packet loss rate and RTT with a neural network prediction model, while in [104] they predicted packet loss rate using a prediction approach called Sparse Basis Prediction Method, developed by Atiya et al. in [105]. In [51] Mehrvar et al. characterized the traffic in ATM networks with a parameter called traffic indicator and used it in combination with neural networks, in order to approximate the actual cell loss rate of various traffic mixtures.

4.1.4 Available Bandwidth Forecast

In Computer Network filed, Available Bandwidth is defined informally as the minimum unused capacity on an end-to-end path, which is a conceptually appealing property with respect to throughput prediction and it is expressed in multiples of bits/second (kilobits/s, megabits/s etc.). It depends on the capacity of the path between client and server, limited by the slowest or (bottleneck) link speed, and on the presence of background or competing traffic, for example congestion. As written in [3], Available Bandwidth can be used, jointly with queuing delay and packet loss, to enhance the TCP throughput prediction of a path. In TCP round-trip delay samples (RTT) and a lowpass filter to predict the smoothed round-trip delay (SRTT) are used to predict both the delay boundary and available bandwidth. In literature there are lots of papers dealing with Available Bandwidth Estimation rather than forecasting, since for prediction purposes most of the attention has focused on throughput. In fact, even tools like Network Wheather Service [69] implements an active measurement methodology that estimates the hop-by-hop available bandwidth between a source and the destination node on a single link, while another tool like Network Bandwidth Predictor (NBP) [46], [28] is able to forecast the available bandwidth, the maximum rate that the path can provide to a flow, without reducing the rate of rest of the traffic in the path. More specifically NBP uses neural networks, with their remarkable ability to learn from examples and derive meaning from complicated or imprecise data, to extract patterns and detect trends of available bandwidth.

4.2 Network Technologies Across The Prediction Field

In this section is provided a "big picture" of the various types of Networks and techniques applied to predict the behavior of network itself .

In most cases the more used network to extrapolate data and then make prediction on it, is the wide area network , in particular Internet.

Among the various type of networks, Internet collects a significant interest in many domains. Predicting internet traffic , or in general WAN traffic, is the first step to improve the design, management and optimization of networks. With an accurate prediction of the network parameters (seen in the previous section) like packet delay,throughput, packet loss and so on, it is possible to design reliable networks ensuring the increase of traffic speed and always better QoS.

On the other hand, many researchers have conducted their studies on different types of networks such as Ad Hoc networks, Wireless Local Area Networks (WLAN), WiMAX and many other with good results. As seen in Chapter 3 we have a lot of techniques that can be applied to perform analysis and data prediction. These techniques could be implemented with all the network topologies but the results will be different among the various types of network. Table 4.5 shows the most used network typology/technique configurations and the most interesting papers who use these configurations to predict network traffic .

Table 4.5: Network typologies

Network	References
WAN	[1, 3, 4, 13, 14, 17, 18, 19, 23, 26, 28, 29, 30] [33, 34, 35, 36, 37, 39, 40, 41, 43, 44, 46, 48, 52] [54, 55, 56, 58, 62, 63, 65, 71, 73, 74]
LAN	[25, 50, 54, 55, 56, 73]
WLAN	[2, 25, 47, 66]
WiMAX	[21, 76]
Ad-Hoc Networks	[11, 20, 25, 68]
Backbone Networks	[31, 41, 53, 67, 70]

4.2.1 Related Works : a Taxonomy

In this section we focus our attention on the most widely used network typology , or rather Wide Area Networks.

Predicting WAN Network Traffic Using Artificial Neural Networks

Since the early nineties ANNs are used to perform forecasting with encouraging results. The basic concept is to train the network with past data to predict future value; as seen in Section 3.3 there were a lot of type of NNs that can be used for our aim (eg. FeedForward , FTDN , Narx ...). Observing previous studies we can say that the most often used NNs type is Multilayer Perceptron Network (MLP) that is a feedforward artificial neural network.

In [36] is shown an Artificial Neural Network based multi-stem ahead forecast method built bye iteratively using 1-ahead prediction as inputs (only past values are used as inputs) and adopting RPROP algorithm [15] in the training stage. They made several experiments based on real-world data from two Internet Service Providers and ,after all, they provide a comparison with other *univariate forecasting (also termed Time Series Forecasting ,TFS)* methods like Holt-Winters 3.2.8 and ARIMA 3.2.4. The results of this comparison show that in general the proposed ANN approach is more powerful and reliable than the other TSF methods.

In [33] the interest is focussed on training algorithms . The aim is to reduce prediction errors using an Artificial Neural Network Prediction model. The comparison between some training algorithms demonstrates the efficiency of Levenberg-Marquardt (LM) and the Resilient back propagation (Rp) algorithms using statistical criteria. Results say that an ANN trained with LM and Rp can successfully be used for the management and prediction of internet traffic over IP networks.

Predicting WAN Network Traffic In Wavelet Domain

The wavelet transform can reduce the complex temporal correlation in the network traffic to short-range dependence in the wavelet domain. The focus of the article [14] is how to exploit the correlation structure to make accurate forecast of the Internet traffic, where the property of self-similarity or long-range dependence [50] plays an important role. First, it is shown that through wavelet transform, the long-range dependence of the temporal network traffic is destructed to short-range dependence among the wavelets. Such short-range dependence can be approximated with linear correlation structure. Also the approximation coefficients can be fairly well forecasted with a linear filter. Then, the method of combining wavelet and recursive least-squares method (RLS) [106] is used to forecast the Internet traffic and is applied to the empirical traffic data from Bellcore LAN, Oct. 1989. The result shows that this new method achieves extraordinary accuracy.

Predicting WAN Network Traffic Using Support Vector Machine

Support vector machines (SVM) have been widely used for pattern recognition, classification, and regression analysis. In [67], Rossi and Bermolen have led a study on efficiency of this technique in prediction field but their results were not very satisfactory in comparison to those obtained with the best-known techniques that use Moving-Average (MA) and Auto-Regressive (AR) models.

The perform an exploration on the use of Support Vector Regression for the purpose of link load forecast: using a hands-on approach,and consequently they tune the SVR performance and compare it with those achievable by using Moving Average (MA) and Auto-Regressive (AR) models. Despite a good accordance with the actual data, the SVR gain achievable over simple prediction methods such as MA or AR is not sufficient to justify its deployment for link load prediction at short time scales. Yet some positive aspects can be found :

- SVR models are rather robust to parameter variation;
- their computational complexity is far from being prohibitive;

Table 4.6: Hybrid models for Network Traffic Prediction

	ANNs	ARIMA	SARIMA*	SVMs	Wavelet	GAs**
Pescapè, Botta et al. [40]	✓				✓	
Pai and Lin [107]		✓		✓		
Chen and Wang [108]			✓	✓		
Armano et al. [109]	✓					✓
Kim and Shin [110]	✓					✓

*SARIMA : Seasonal ARIMA ; ** GAs : Generic Algorithms

- the cascading of SVR models may significantly extend the achievable forecast horizon, entailing only a very limited accuracy degradation.

Predicting WAN Network Traffic Using Hybrid Methods

In the literature, different combination techniques have been proposed in order to overcome the deficiencies of single models. The basic idea of the model combination in forecasting is to use each models unique feature in order to capture different patterns in the data. The difference between these combination techniques can be described using terminology developed by the classification and neural network literature [111]. Hybrid models can be homogeneous, such as using differently configured neural networks (all multi-layer perceptrons), or heterogeneous, such as with both linear and nonlinear models [112]. In recent years, several hybrid models have been proposed, using autoregressive integrated moving average (ARIMA) and artificial neural networks (ANNs) and applied to time series forecasting with good performance. In [8] Feng et al propose an hybrid model considers the routine time prediction technique like AR, ANN or any others as atomic building block. A linear hybrid technique is used to combine their forecast result into the final result. Table 4.6 shows a few articles that use an hybrid model to perform a forecast.

The above mentioned references are referred to a time series prediction and forecasting but these models may be applied with very good result also to internet traffic prediction and forecasting since we can characterize internet traffic as a time series.

4.3 Error and Performance Metrics

Error and performance metrics are used to calculate the difference between the predicted and target value, and respectively to measure the performance of the whole prediction system.

From the wide literature analyzed we can say that various types of error are used in a wide range of statistical and probabilistic studies.

Two of the most popular error metrics are the Sum Square Error (SSE) and Mean Square Error (MSE) that are defined as:

$$SSE = \sum_{j=1}^{N} (y_j - \hat{y}_j)^2 \,,$$

$$MSE = \frac{1}{N} \sum_{j=1}^{N} (y_j - \hat{y}_j)^2 \,,$$

where N is the size of dataset , y_j is the actual value and $\hat{y}_j$ is the predicted value (assumption yet valid for all following error metrics).

The Root Mean Square Error (RMSE) is derived from the MSE and is given in the following formula:

$$RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (y_j - \hat{y}_j)^2} \,.$$

The (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. Its denote the square root of the variance, known as the standard deviation.

Other two commonly used quantity , to measure how close forecasts or predictions are to the eventual outcomes, are the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), both defined as follows:

$$MAE = \frac{1}{N} \sum_{j=1}^{N} |y_j - \hat{y}_j| \,,$$

$$MAPE = \frac{100}{N} \sum_{j=1}^{N} \left| \frac{y_j - \hat{y}_j}{y_j} \right| \,.$$

The MAPE is measure of accuracy in a fitted time series value in statistics, specifically trending, and it usually expresses accuracy as a percentage.

Table 4.7: Error Metrics in Prediction Fields

Parameters	References
SSE	[41]
MSE	[11, 43, 66, 60, 19, 45, 72]
RMSE	[67, 18, 70, 8, 23, 56, 49, 55, 5]
NMSE	[8, 66, 60, 52, 53, 49]
MMSE	[19, 55]
MAE	[60, 44]
MAPE	[36, 8, 23, 1]
RPE	[13, 3, 49, 73]

Normalized Mean Square Error (NMSE) is given by the following expression :

$$NMSE = \frac{\sum_{j=1}^{N}(y_j - \hat{y}_j)^2}{\sum_{j=1}^{N}(y_j - \overline{y}_j)^2},$$

where $\overline{y}_j$ is the mean of y_j.

Finally, Relative Prediction Error (RPE) and Mean Relative Prediction Error (MRPE) are defined as follow :

$$RPE = \frac{\hat{y} - y}{min(y, \hat{y})},$$

$$MRPE = \frac{1}{N}\sum_{j=1}^{N}\frac{\hat{y}_j - y_j}{min(y_j, \hat{y}_j)}.$$

In Table 4.7 are represented all the errors seen before and the papers that use these errors for an estimation of prediction error and performance.

In testing phase of this work were used only RMSE, MAE and MAPE metrics.

RMSE and MAE are *scale-dependent* error measures , in other words means that these two metrics are useful when comparing different methods applied to the same set of data , in contrast with the MAPE that have the advantage of being *scale-independent*, and so are frequently used to compare forecast performance across different data sets. However , the MAPE has the disadvantage of being infinite or undefined if $y_j = 0$ for any t in the period of interest.

Chapter 5

Platforms and Toolkits

Without doubts, the most popular tool used in papers reviewed in this work is Matlab. It has both Neural Network Toolbox, in order to make forecasts with ANN, and System Identification Toolbox for studies with model-based approach. Neither MATLAB, nor any of the toolboxes, contain a function that does ARIMA or HoltWinters modeling, other tools are used in this field. R is the most popular and complete tool from this point of view. Other tool are used for prediction purpose, such as ITSM (Interactive Time Series Modelling [116]), Weka (machine learning software written in Java [117]), various proprietary solutions developed in Java, Fortran or C [74, 53] or stand alone products like Network Weather Service [45, 69]. Not all papers focus on real data. Some of them ([42, 59, 38]) make simulations using software like ns-2 [118] or OPNET [23, 16]. In table 5.1 there is a taxonomy according to most of the tools which are used.

5.1 The MATrix LABoratory : MatLab

MATLAB (MATrix LABoratory) [126] is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numeric computation. It is a very powerful

Table 5.1: Most used tools

Tool	References
Matlab	[43, 40, 33, 8, 6, 64, 21, 68, 76, 2, 52, 48, 65, 54]
Weka	[46, 28, 58, 35]
R/Splus	[70],[4],[13],[41]
ITSM	[31, 41]
ns2	[42, 59, 38]

solution to solve technical computing problems faster than with traditional programming languages, such as C, C++, and Fortran

5.1.1 The MATLAB System

Matlab is available for MS Windows personal computers and Macintosh ,and UNIX and Linux systems. Matlab is compatible in all these platforms, which means that users of Matlab can share ideas, programs and processing techniques. Matlab is not only a programming language but also a software environment that allows you to efficiently use this language . The interactive environment of Matlab allows you to manage variables, import and export data, perform calculations, create charts, develop and manage files use with Matlab.

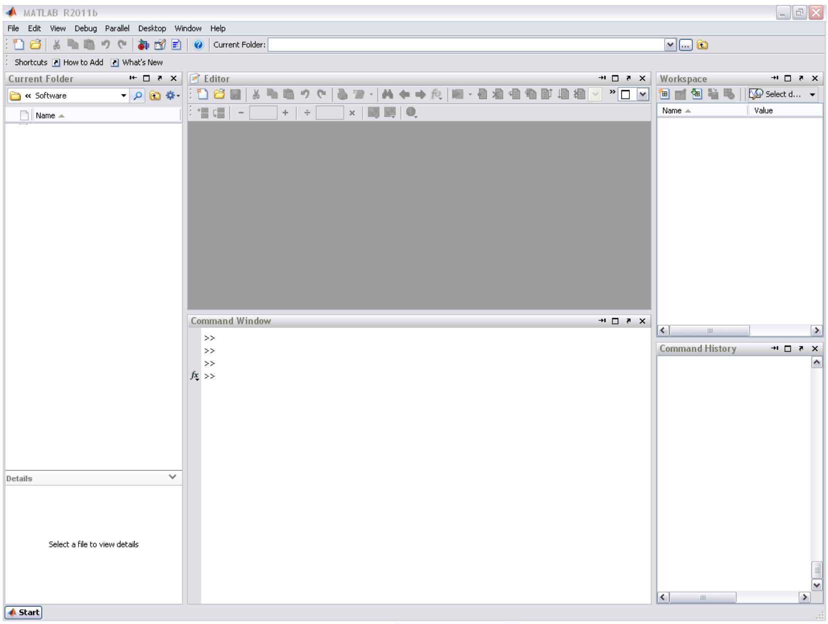


Figure 5.1: Desktop Tools and Development Environment

The MATLAB system consists of these main parts:

Desktop Tools and Development Environment

This part consist in a set of tools and facilities that help you use MATLAB functions and files. Many of these tools are graphical user interfaces (GUI). It includes: the MATLAB desktop and Command Window, an editor and debugger, a code analyzer, and browsers for viewing help, the workspace, and folders.

Mathematical Function Library

This library is a collection of computational algorithms ranging from elementary functions, like sum, sine, cosine, and complex arithmetic, to more sophisticated functions like matrix inverse, matrix eigenvalues, fast Fourier transforms an many other.

The Language

The MATLAB language is a high-level matrix/array language with control flow statements, functions, data structures, input/output, and object-oriented programming features. It allows both "programming in the small" to rapidly create quick programs you do not intend to reuse. You can also do "programming in the large" to create complex application programs intended for reuse.

Graphics

MATLAB has extensive facilities for displaying vectors and matrices as graphs, as well as annotating and printing these graphs. It includes high-level functions for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics. It also includes low-level functions that allow you to fully customize the appearance of graphics as well as to build complete graphical user interfaces on your MATLAB applications.

External Interfaces

The external interfaces library allows you to write C/C++ and Fortran programs that interact with MATLAB. It includes facilities for calling routines from MATLAB (dynamic linking), for calling MATLAB as a computational engine, and for reading and writing MAT-files.

5.1.2 ToolBox

Matlab includes several additional software modules, called "toolbox", which perform specialized tasks. Although you can buy there separately toolbox, we must have the use of Matlab main program. Currently, there are a lot of toolbox that can help in many application fields like fuzzy logic , financial analysis, design of control systems and signal processing and image. A full list is available on the website of Math Works.

5.1.3 System Identification Toolbox

System Identification Toolbox contains a set of instruments in order to identify linear model from a data set of a time domain or frequency domain. It allows identification of first, second and third order continuous time models. System Identification Toolbox implements a GUI for data Analysis and Preprocessing, model estimation based on data-set, model analysis and result exporting in Matlab workspace. Opening System Identification Toolbox is done typing *ident* in Matlab command window. This command allows to run the graphical interface shown in Figure 5.2. *Data Views* area contains all data set that are to be imported in the toolbox. It is possible preprocessing all data dragging them in the *Working Data* area. Estimation is done selecting *Estimate* voice in the 4th menu, while it is possible to make validation in the *Validation Data* area. Results are visible in *Model Views* area. System Identification Toolbox allows also command line instructions to operate with time-series. You can also estimate parametric autoregressive (AR), autoregressive and moving average (ARMA), and state-space time-series models. Neither MATLAB, nor any of the toolboxes, contain a function that does ARIMA modeling. From this point of view it is better to use other tools like the R environment.

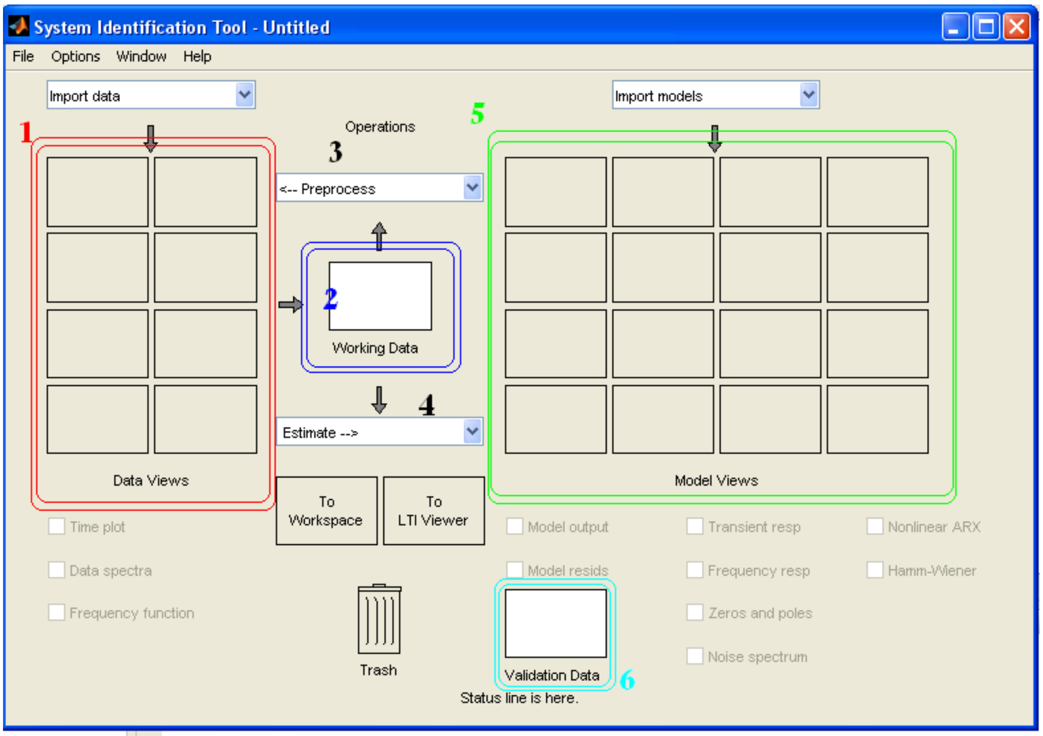


Figure 5.2: Ident GUI

System Identification Toolbox: A practical example

Let's suppose to import a time series in the array *data*.

Let's create the *data*1 array that is half of *data* array.

```
data1=data(1:((length(data)-1)/2));
```

Then that's transform array format in iddata format

```
y=iddata(data,[],0.05);
y1=iddata(data1,[],0.05);
```

Next, let's estimate an AR model based on the first half of the data, and let's evaluate the four step-ahead predictions on the second half.

```
m=ar(y1,4);
```

Next, let's evaluate a forecasting procedure based on estimated model m with the commands:

```
k=6;
yhat=predict(m,y,k);
```

k: The prediction horizon. Old outputs up to time t-k are used to predict the output at time t. The command k = Inf gives a pure simulation of the system.(Default k=1) With command:

```
plot(y,yhat)
```

we have the plot showed in figure 5.3.

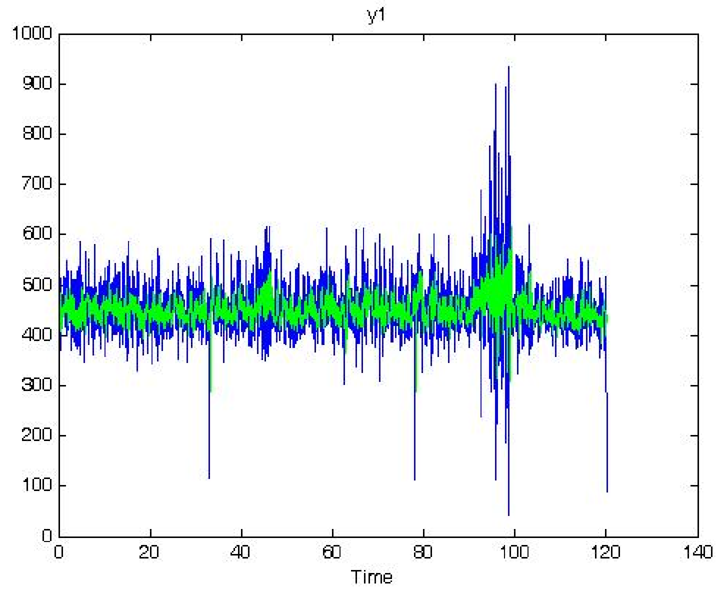


Figure 5.3: Simulation of AR System

5.1.4 Neural Network Toolbox

Neural Network Toolbox (NNet) [114] provides tools for designing, implementing, visualizing, and simulating neural networks. NNet includes command-line functions and graphical tools (nntool Figure 5.4) for creating, training, and simulating neural networks. Graphical tools make it easy to develop neural networks for tasks such as data fitting (including time-series data), pattern recognition, and clustering. After creating your networks in these tools, you can automatically generate the MATLAB code to capture your work and automate tasks.

Key Features:

- *Neural network design, training, and simulation*
- *Pattern recognition, clustering, and data-fitting tools*
- *Supervised networks including feedforward, radial basis, LVQ, time delay, nonlinear autoregressive (NARX), and layer-recurrent*
- *Unsupervised networks including self-organizing maps and competitive layers*
- *Preprocessing and postprocessing for improving the efficiency of network training and assessing network performance*

- *Modular network representation for managing and visualizing networks of arbitrary size*
- *Routines for improving generalization to prevent overfitting*
- *Simulink blocks for building and evaluating neural networks, and advanced blocks for control systems applications*

Here it is the Matlab command to open the toolbox GUI :

```
>> nntool
>>
```

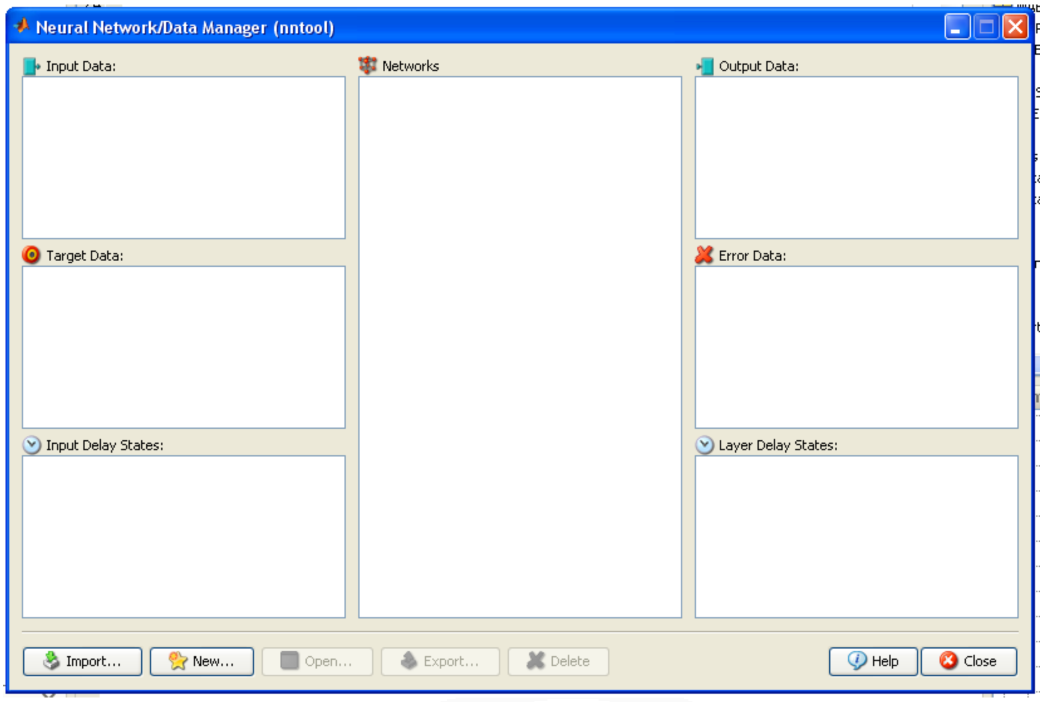


Figure 5.4: GUI of Neural Network Toolbox

5.1.5 Predicting ”future” with NNToolbox

In order to make a prediction of future values of data is necessary to design a neural network. There is a simple workflow to be followed in the design process using the NNet toolbox.

- Collect data

- Create the network
- Configure the network
- Initialize the weights and biases
- Train the network
- Validate the network
- Use the network

In prediction field the most used and powerful neural networks are the Focused Time-Delay Neural Network (FTDNN) and the Non-linear Autoregressive Network with eXogenous inputs (NARX).

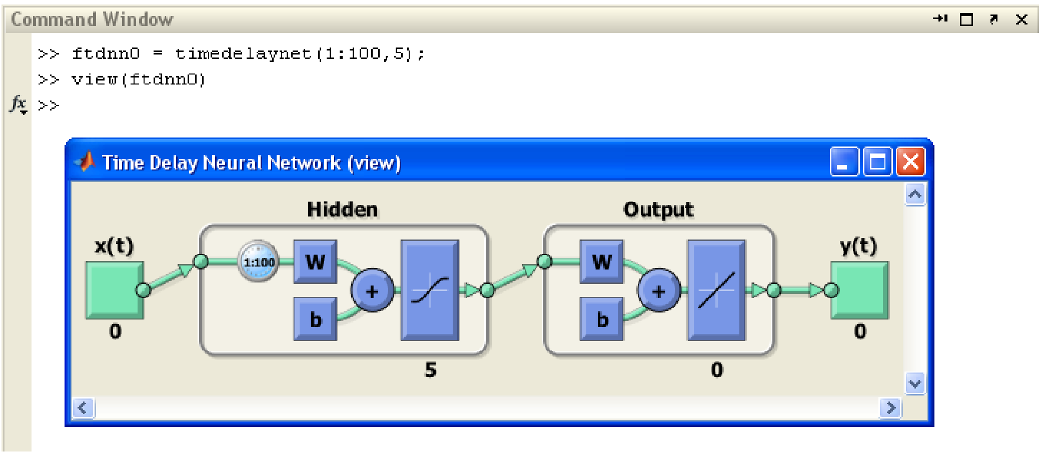


Figure 5.5: Matlab commands to create and visualize an FTDNN

In Figure 5.5 are shown the commands to create and then visualize a Focused Time-Delay Neural Network . The same is shown for a NARX Network in Figure 5.6 , in this case the two configuration S-P and P of NARX are shown (see section 3.3.7).

A particular interest must be dedicated to two very significant and important parameters to perform a good prediction. The first is the **transfer function** (see Section 3.3.1) associated with a single node. The neurons can use different transfer functions to generate their output. There are three most used transfer functions for multilayer networks :

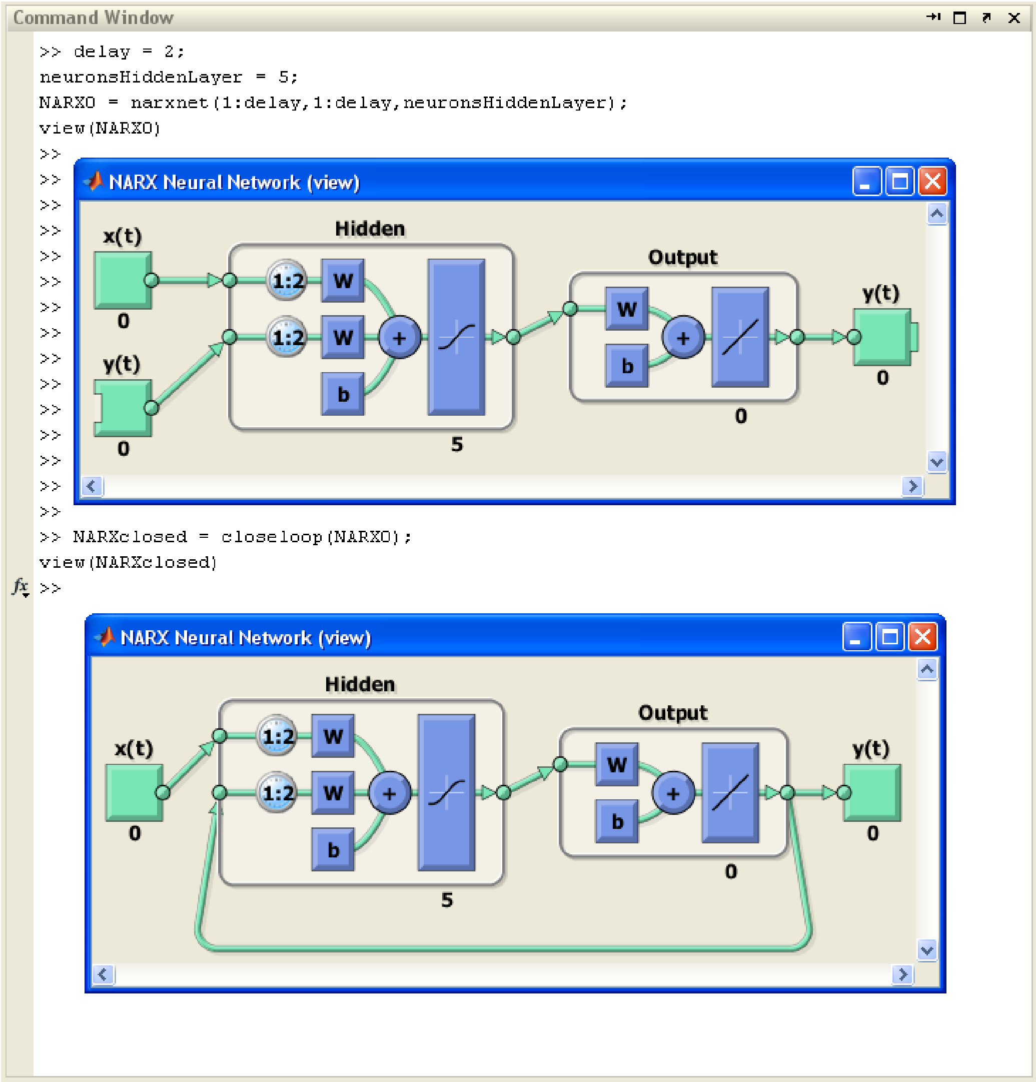


Figure 5.6: Matlab commands to create and visualize a NARX

1. Log-Sigmoid (logsig)
2. Tan-Sigmoid (tabsug)
3. Linear (purelin)

The second , but not less important , parameter of interest is the Training Algorithm chosen to train the network during the learning phase. The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performances.

Considering the *Gradient descent* algorithm , the training phase consist of updating the network weights and biases in the direction in which the performance function decreases more rapidly the negative of the gradient. One iteration of this algorithm can be written as:

$$x_{j+1} = x_j - \alpha_k g_k,$$

where x_j is a vector of current weights and biases , g_k is the current gradient , and α_k is the learning rate. This equation is iterated until the network converges.

A list of the training algorithms that are available in the Neural Network Toolbox software , and which use gradient-based or Jacobian-based methods [115] , is shown in Table 5.2 .

Table 5.2: Training Algorithms in Neural Network Toolbox software

NNTool parameter	Algorithm
trainlm	Levenberg-Marquardt
trainbr	Bayesian Regularization
trainbfg	BFGS Quasi-Newton
trainrp	Resilient Backpropagation
trainscg	Scaled Conjugate Gradient
traincgb	Conjugate Gradient with Powell/Beale Restarts
traincgf	Fletcher-Powell Conjugate Gradient
traincgp	Polak-Ribiére Conjugate Gradient
trainoss	One Step Secant
traingdx	Variable Learning Rate Gradient Descent
traingdm	Gradient Descent with Momentum
traingd	Gradient Descent

The fastest training function is *trainlm*. In [115] there is also a clear and detailed survey of basic neural network architectures and learning rules. Several *methods of training* networks are emphasizes. It is also important to choose an appropriate training function due to avoid long training times or large memory need. So a training function can be more suitable than another depending on the type of problem that we want to deal with. Generally, trainlm is the fastest training function and it is the default function in most of neural networks. For simulation and testing phase we have used the *"trainbfg"* function.

To train a Neural Network in Matlab there is the command :

```
[NET,TR] = train(NET,X,T,Xi,Ai)
```

This Matlab function takes a network object NET, input data X and target data T and returns the same network object NET and a training record TR at the end of training. Xi and Ai are the initial input and layer delays states respectively. The function *train* calls the network training function *NET.trainFcn* with the parameters *NET.trainParam* to perform training. So , before train function it is possible to set.

Parameter	Stopping Criteria
min_grad	Minimum Gradient Magnitude
max_fail	Maximum Number of Validation Increases
time	Maximum Training Time
goal	Minimum Performance Value
epochs	Maximum Number of Training Epochs (Iterations)

Table 5.3: Training stopping Criteria

We must raise interest on the performance metrics, the magnitude of the gradient of performance and the number of validation checks. The magnitude of the gradient and the number of validation checks are used to terminate the training. The gradient will become very small as the training reaches a minimum of the performance. If the magnitude of the gradient is less than 1e-5, the training will stop. This limit can be adjusted by setting the parameter net.trainParam.min_grad. The number of validation checks represent the number of successive iterations that the validation performance fails to decrease. If this number reaches 6 (the default value), the training will stop. In this run, you can see that the training did stop because of the number of validation checks. You can change this criterion by setting the parameter net.trainParam.max_fail.

There are other criteria that can be used to stop network training. They are listed in the table 5.3. The training window will appear during training, as shown in the figure 5.7.

When the training procedure as finished we can plot some interesting results to analyze the training, like Time-series Response (Figure 5.9 and 5.11) , Best Training Performance (Figure 5.8) for FTDN Network and Best Validation Performance (Figure 5.10) for NARX Networks.

The figure 5.10 doesn't indicate any major problems with the training. The validation and test curves are very similar. If the test curve had increased significantly before the validation curve increased, then it is possible that some overfitting might have occurred.

After the network is trained and validated, the network object can be used to calculate the network response to any input :

```
NET = net(data);
```

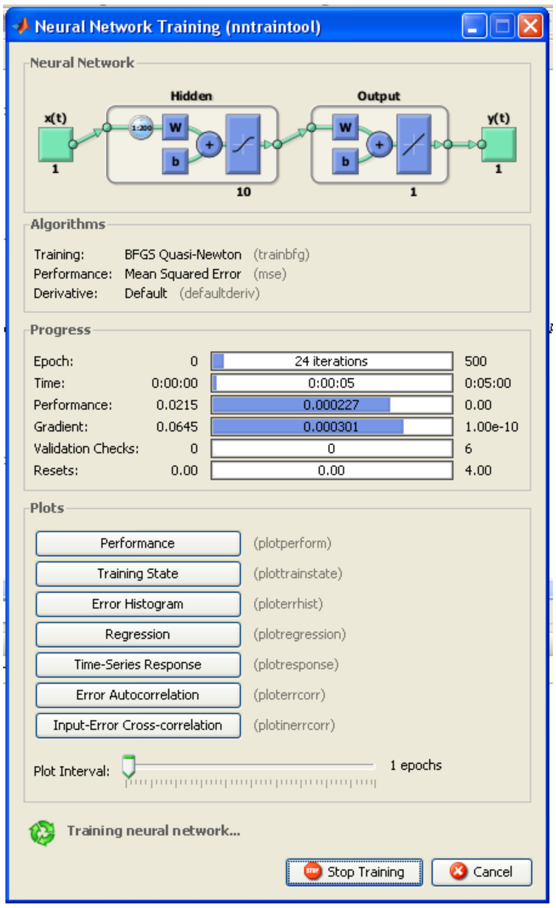


Figure 5.7: Training window

Note that *data* must be a column cell vector.

In the Neural Networks Toolbox of Matlab there are three Performance functions.The first is **MAE** , it measures network performance as the mean of absolute errors. The other two are **MSE** (default) and **SSE** that can provide a network performance according to the mean of squared errors and sum of squared errors respectively. See Section 4.3 for references.

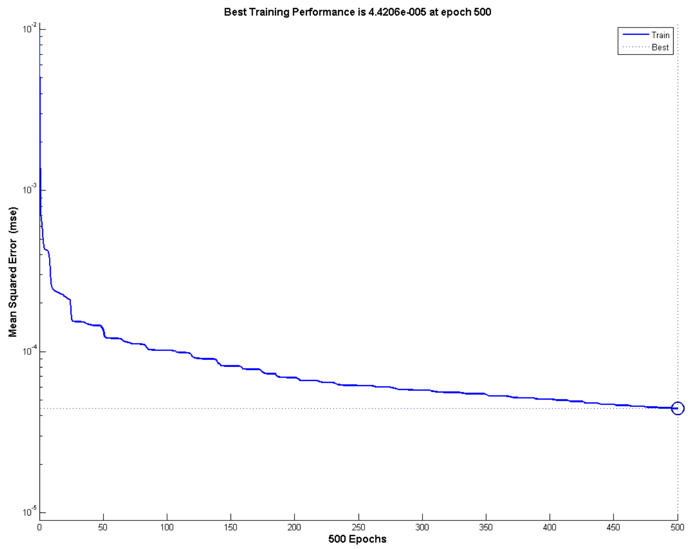


Figure 5.8: Best Training Performance

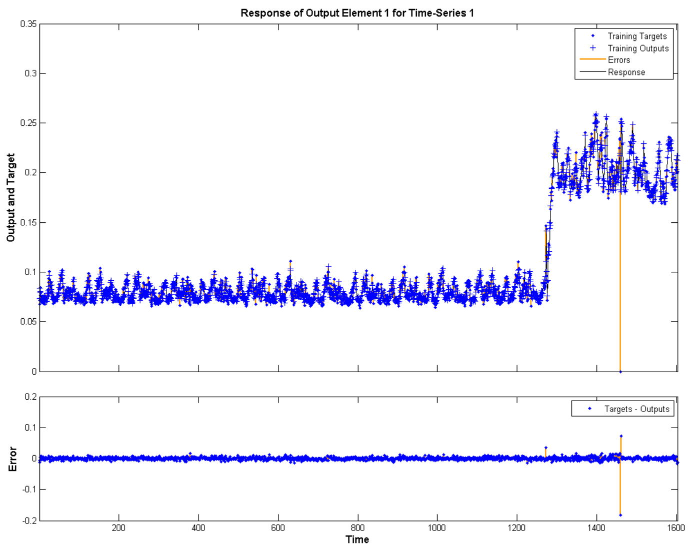


Figure 5.9: Time-series Response of a *timedelaynet* Training

5.2 The R-project

R is a very popular environment for statistical analysis. It was introduced in 1996 by Ross Ihaka and Robert Gentleman (University of Auckland, New

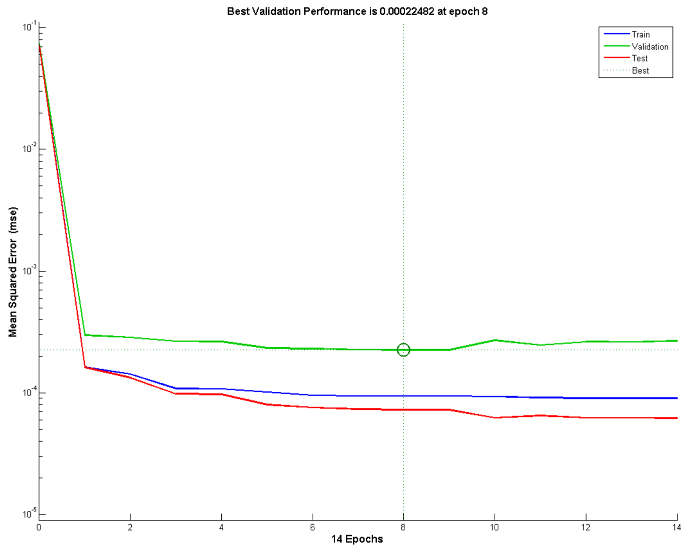


Figure 5.10: Best Validation Performance

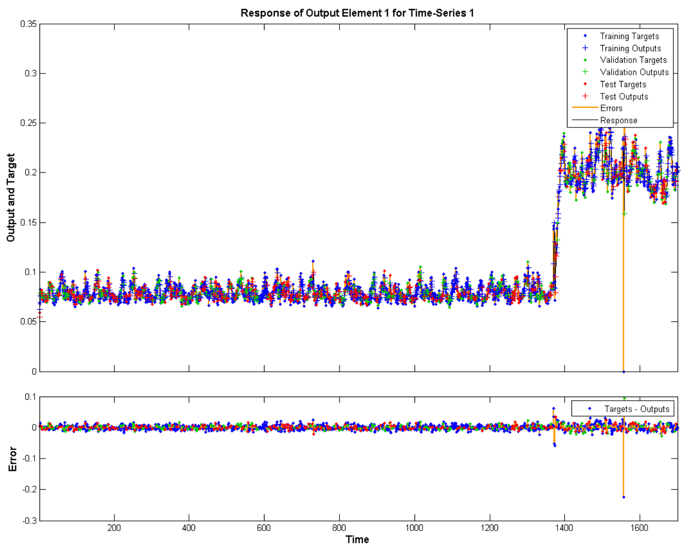


Figure 5.11: Time-series Response of a *narxnet* Training

Zealand) and now, R is developed by the R Development Core Team, of which Chambers is a member. R is named partly after the first names of the first two R authors (Robert Gentleman and Ross Ihaka), and partly as a play on the name of the S programming language, appeared in 1976. Since its birth, R has gained many users and contributors, which continuously develop new add-ons called packages. R is an opensource project and is part of the GNU project. The source code for the R software environment, which is written primarily in C, Fortran, and R, is freely available under the GNU General Public License, and pre-compiled binary versions are provided for various operating systems (GNU/Linux, Windows, etc). R uses a command line interface; however, several graphical user interfaces are available for use with R. It is distributed by the Comprehensive R Archive Network (CRAN) and it is available from the url: http://cran.r-project.org. Actually the stable release is 2.14.1 dated December 22, 2011.The R Environment includes:

The R Environment includes:

- an effective data handling and storage facility,
- a suite of operators for calculations on arrays, in particular matrices,
- a large, coherent, integrated collection of intermediate tools for data analysis,
- graphical facilities for data analysis and display either on-screen or on hardcopy,
- a well-developed, simple and effective programming language which includes conditionals, loops, user-defined recursive functions and input and output facilities.

In the 4th Annual Rexer Analytics Data Miner Survey (2010), in the TOOL Highlights is written:

> *"After a steady rise across the past few years, the open source data mining software R overtook other tools to become the tool used by more data miners (43%) than any other."*

Also R has many functions for time series analysis with ARMA, ARIMA, SVM, HoltWinters models and it is our principal choice for time-series analysis in formula-based field.

5.2.1 Time-Series representation and functions

For our purposes we used forecast package and e1071 package. First implements all functions to use with ARMA, ARIMA, HoltWinters models. In particular with the function *auto.arima()* it is possible to find automatically the indexes p, d, q of an ARIMA(p, d, q) model. HoltWinters() is able to forecast time series with Holt-Winters algorithm. The e1071 package include the implementation od SVM in R. The svm() function in e1071 provides an interface to libsvm along with visualization and parameter tuning methods.

Function $ts()$

In R environment the function $ts()$ is used to create time-series objects. These are vector or matrices with class of "ts" (and additional attributes) which represent data which has been sampled at equispaced points in time. Time series must have at least one observation, and although they need not be numeric there is very limited support for non-numeric series. ts() objects are used in most functions of forecasting package.

Function $auto.arima()$

The $auto.arima()$ function is part of the forecast package. This function returns best ARIMA model according to either AIC, AICc or BIC value. The function conducts a search over possible model within the order constraints provided.

Function $HoltWinters()$

The $HoltWinters()$ function computes Holt-Winters Filtering of a given time series. Unknown parameters are determined by minimizing the squared prediction error.

Function $ets()$

ETS can be considered an abbreviation of ExponenTial Smoothing. The ets() function found in the forecast package can be used to specify the model or to automatically select a model.

Function $forecast()$

forecast() is a generic function for forecasting from time series or time series models. The function invokes particular methods which depend on the class of the first argument. It takes a time series or time series model as its main argument. If first argument is class ts, returns forecasts from automatic ETS algorithm if non-seasonal or seasonal period is less than 13.

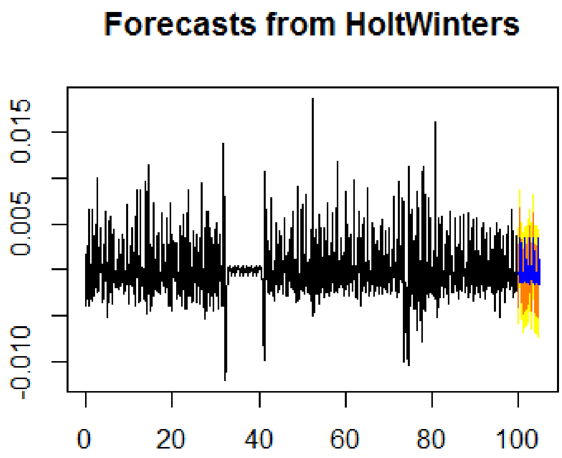


Figure 5.12: *forecast*() function

As shown in Figure 5.12 , the forecast values are shown as a blue line, and the orange and yellow shaded areas show 80% and 95% prediction intervals, respectively.

5.2.2 Forecasting with R:A practical example

After loading the *forecast* package and after setting the local working directory we can start with our example. Let's suppose to import a time series in the *data* array.

```
dati=scan("dati.dat")
```

Next, we encapsulate the array in a time-series object, with deltat=0.5

```
dati.ts=ts(dati,start=0,deltat=0.05)
```

After that, we use the *auto.arima*() function

```
model=auto.arima(dati.ts)
> model
Series: dati.ts
ARIMA(5,1,4)(1,0,2)[20]

Coefficients:
         ar1      ar2     ar3     ar4      ar5
      0.9680  -0.0002  0.0033  0.1594  -0.2448
```

```
s.e.    0.0232     0.0349    0.0352    0.0320     0.0217
            ma1         ma2         ma3        ma4
        -0.0355    -0.0327    -0.0342    0.8322
s.e.     0.0155     0.0196     0.0158    0.0105
           sar1        sma1        sma2
        -0.4231    -0.1819    -0.3245
s.e.     0.1692     0.1665     0.1034

sigma^2 estimated as 1325:  log likelihood=-12041.83
AIC=24109.66    AICc=24109.81    BIC=24184.84
```

then we make a forecast with prediction horizon h=100 and then we plot the results in Figure 5.13:

```
dati.forecast=forecast(model,h=100)
plot(dati.forecast)
```

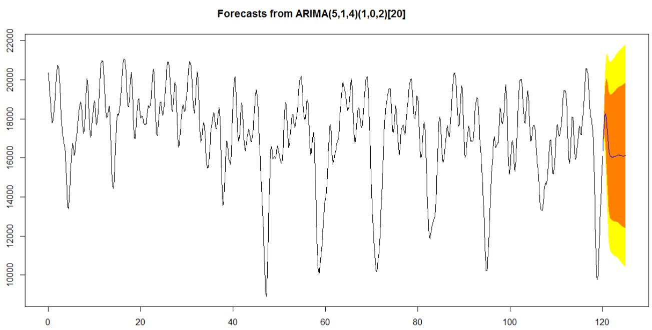


Figure 5.13: $forecast()$ function with $auto.arima()$

Chapter 6

Comparison of different techniques

6.1 Testbed

6.1.1 Data Sets

Data sets are obtained from Heterogenous Networks Data Traces and MagNets data traces Sections of GRID Unina Website [119] and from SANET Networks data traces Section of SANET website [122]

Heterogenous Networks Data Traces Section contains data traces from real networks obtained using D-ITG [120]. Each archive is in tar.gz format and contains files with samples of measured QoS parameters related to several end-to-end paths. The considered QoS parameters are packet loss, delay, and jitter. Samples are obtained by adopting an active measurement approach, sending probe packets by using D-ITG with a packet rate of 100 pps. File names have the following format:

xxx-to-yyy-ttll[-ddee]-ppp.tar.gz

where:

- **xxx**= Access network at sender side (with the term wired we mean 100 Mbps Ethernet connection; ADSL is an 640 Kbps connection; with the term wireless we mean 802.11b connection (ap = access point, ah = ad hoc mode))

- **yyy**= Access network at receiver side (with the term wired we mean 100 Mbps Ethernet connection; ADSL is an 640 Kbps connection; with the term wireless we mean 802.11b connection (ap = access point, ah = ad hoc mode))

- **tt**: Operating System at Sender Side (with the term Win we mean Win32 OS; with the term lin we mean Linux OS)
- **ll**: Operating System at Receiver Side (with the term Win we mean Win32 OS; with the term lin we mean Linux OS)
- **dd**: Device at Sender Side (with the term lap we mean laptop; with the term ws we mean workstation). It is an optional field.
- **ee**: Device at Receiver Side (with the term lap we mean laptop; with the term ws we mean workstation). It is an optional field.
- **ppp**: Used Protocol (TCP, UDP, or SCTP)

Each archive contains several files with the indication of the:

- used packet size (64, 512, 1024 bytes)
- measured QoS parameter (packet loss, delay, or jitter).

Each sample is calculated using non-overlapping windows of 10ms length.

In this test following packages are used with 64 bytes packet size :

- gprs-to-wired-winlin-tcp.log.tar.gz
- gprs-to-wired-winlin-udp.log.tar.gz

As example, Figure 6.1 shows the representation of gprs-to-wired-winlin-tcp dataset.

MagNets Data Traces Section contains data traces from the MAGNETS network backbone [121] obtained using D-ITG [120]. The traces have been collected during a joint research activity between University of Napoli Federico II and the Network Group of the Deutsche Telekom Laboratories in Berlin. Each archive contains files with samples of QoS parameters measured over four end-to-end paths. The considered QoS parameters are throughput, packet loss, delay (RTT), and jitter. Samples are obtained, by adopting an active measurement approach, sending probe packets using two packet rates (128 pps and 11000 pps) and packet size of 1024 Bytes. For each path and for each QoS parameter, 20 tests have been performed. File names have the following format:

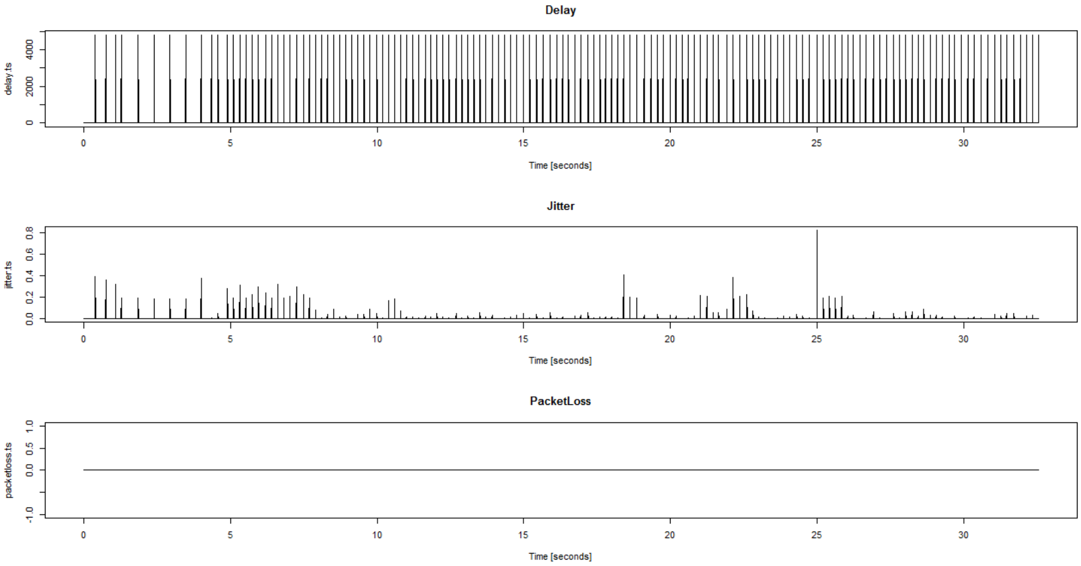


Figure 6.1: Gprs-to-wired-winlin-tcp dataset

xxx-to-yyy-ppp.tar.gz

where

- **xxx** = Sender node
- **yyy** = Receiver node
- **ppp** = Packet rate (128 pps or 11000 pps)

Each archive contains several files with the indication of the:

- measured QoS parameter (throughput, packet loss, delay, or jitter);
- used protocol (TCP or UDP);
- iteration number (1 to 20).

Each sample is calculated using non-overlapping windows of 50ms length. In this study Short-Term HHI-TC-11000 TCP and UDP iteration 1 Trace is used.

SANET is an independent civil association, members of which agreed with conditions to provide each other with Internet services. It is a non-profit organization whose members contribute to operation of the network. SANET is not the organization managed by the Ministry of Education of the Slovak Republic. Data traces are obtained using MRTG [123], a free software for monitoring and measuring the traffic load on network links. MRTG is written in Perl and can run on Windows, Linux, Unix, Mac OS and NetWare. It allows the user to see traffic load on a network over time in graphical form. Data traces for this test are taken from Port1 log of website [122] and were last updated on Wednesday, 22 February 2012 at 11:17, at which time the network 'L2-SIX-KE' had been up for 396 days, 5:39:46. More infirmations on data trace are written as follows:

- System: UVT TU Kosice
- Interface: GigabitEthernet
- Ip: 192.108.145.10
- Max Speed: 1 Gbit/s

A single data trace is composed by several sub traces:

- Daily traces: sampled every 5 minutes;
- Weekly traces: sampled every 30 hours;
- Monthly traces: sampled every 2 hours;
- Yearly traces: sampled every 1 day;

A better overview with forecasts is showed in Table 6.1

Table 6.1: SANET Data Traces: sampling and forecasts

Period	**Sampling**	**Prediction**	
		Horizon 50	Horizon 100
Day	5m	250m	500m
Week	30m	25h	50h
Month	2h	100h	200h
Year	1d	50d	100d

With SANET traces was not possible to make predictions using Holt-Winters models, since the algorithm was crashed.

6.1.2 Techniques and Errors

From the point of view of used techniques, the choices for this study are ARIMA models, Holt-Winters models, FTDNN and NARX networks. ARIMA and Holt-Winters models performance evaluation are implemented through R software. ARIMA models are found using function *auto.arima*() that automatically returns best ARIMA model according to either AIC, AICc or BIC value. Holt-Winters models are found using $HoltWinters()$ function whose beta and gamma parameters are determined by minimizing the squared prediction error. Forecasts are generated with $forecast()$ function. During representation, predicted values are plotted as a blue line, the 80% prediction interval as an orange shaded area, and the 95% prediction interval as a yellow shaded area. R software is also used to implement component decomposition (Section 6.1.3) through the function *stl*() (see Section 5.2.1). Implementation of Neural Networks issues are made through MatLab and Neural Network Toolbox.

Settings for FTDNN Neural Networks are:

```
Network settings:
timedelaynet with a tapped delay line (delay from 1 to H)
and 5 neurons in the hidden layer.

Training settings:
ftdnn0.trainFcn = 'trainbfg'; % (training function)
ftdnn0.dividefcn=' ';
ftdnn0.trainParam.epochs = 1000; % maximum number of iterations
ftdnn0.trainParam.time = 300; % maximum training time in sec
ftdnn0.trainParam.min\_grad = 1e-10; % minimum Gradient Magnitude
```

Settings for NARX Neural Networks are:

```
Network settings:
narxnet with 5 neurons in each hidden layer.

Training settings:
net.trainFcn = 'trainbfg'; % training function
net.dividefcn=' ';
net.trainParam.epochs = 1000; % maximum number of iterations
net.trainParam.time = 300; % maximum training time in sec
net.trainParam.min\_grad = 1e-10; % minimum Gradient Magnitude
```

Performance evaluation is made calculating different kinds of error. The choice of parameters for this study is for RMSE, MAE, MAPE. RMSE is generally preferred to the MSE as it is on the same scale as the data. Historically, the RMSE and MSE have been popular, largely because of their theoretical relevance in statistical modelling. But they are more sensitive than MAE to outliers, which has led some authors to recommend against their use in forecast accuracy evaluation. MAPE has the disadvantage of being infinite or undefined if the forecast value is zero. MAE is preferred because it is simpler to explain but it remains a problem making a comparison between time series forecasts that are on different scales. For this reason it's convenient to normalize the value of MAE, having the MAEN. In formulas:

$$MAEN = \frac{MAE}{max(|\{y_j\}|)} = \frac{mean(|y_j - \hat{y}_j|)}{max(|\{y_j\}|)}$$

where $\{y_j\}$ is the dataset, y_j is the actual value and $\hat{y}_j$ is the predicted value. Main advantages of using MAEN are:

- better performance evaluation, compared to the scale of the actual dataset;
- better individuation of techniques that haven't got good performances, with MAEN values greater than one;
- better comparison between performance of different parameters and different dataset components;

6.1.3 Data set decomposition

In case of MagNets Short-Term HHI-TC-11000 TCP and UDP iteration 1 Trace and SANET traces, a decomposition algorithm is used in order to extract main components of a time series z_t:

- T_t, the trend component. It reflects the long term progression of the series;
- S_t, the seasonal component. It reflects the repetitive and predictable movement around the trend component;
- e_t, the remainder component.

This decomposition is made using *stl*() function in R, described in Section 5.2.1, and Matlab. An example of *stl*() result is shown in Figure 6.2. In case of MagNets traces the evaluation of seasonal component was excluded, since data values were related to few minutes of sampling. In case of SANET traces all components were evaluated, since data are referred to different days, weeks and months.

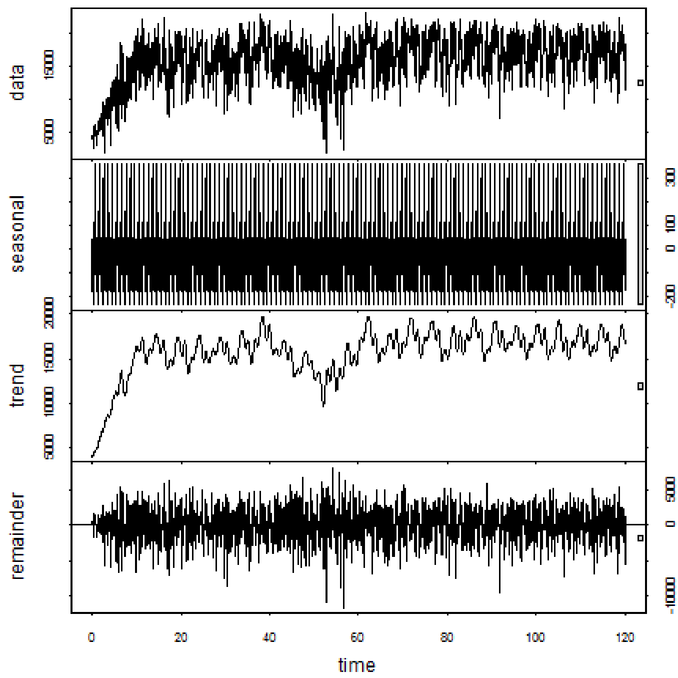


Figure 6.2: Decomposition of a Time-Series using *stl*() function in R

6.2 Results and Errors Evaluation

6.2.1 GPRS-to-wired traces

In Table 6.5 are shown the performance metrics related to the short-term traces obtained from Heterogenous Networks Data Traces.

Let's do a detailed analysis on the following data packages:

- gprs-to-wired-winlin-tcp.log.tar.gz
- gprs-to-wired-winlin-udp.log.tar.gz

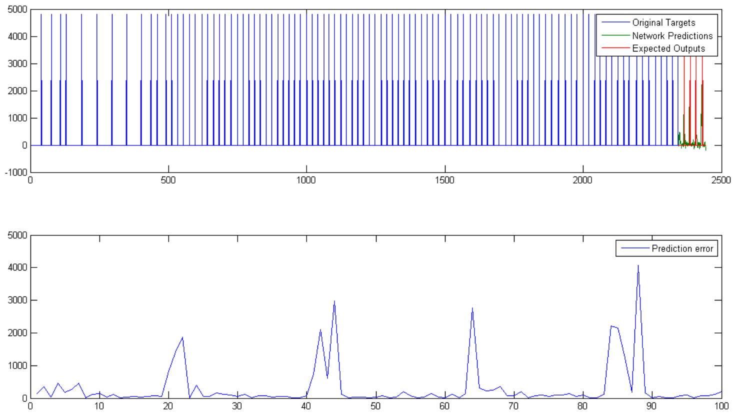
These two Traces are obtained from a gprs access network, with Win32 OS at sender side, to a wired access network using Linux OS at receiver side. Both TCP and UDP protocol are traced.

Predictions were made for the Delay, Jitter and Packet Loss parameters. After that, it was extrapolated the MAE performance and then we calculated the normalized MAE (MAEN).

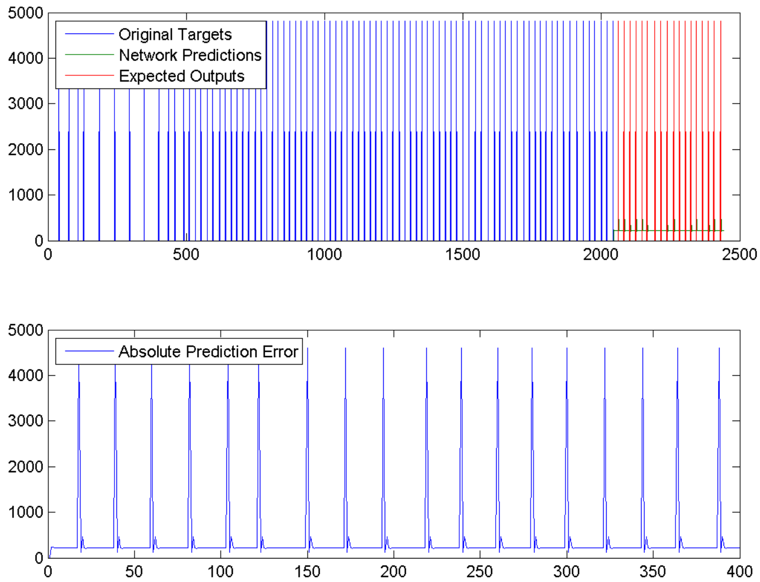
The resultant MAEN values are shown in Table 6.6 (MAEN_TCP for TCP data and MAEN_UDP for UDP data). Analyzing this Table and focusing on Delay parameter and FTDNN technique, the worst value occur on prediction horizon H400_UDP. For H=100 we have the best value (See Figure 6.3(a)) and, in general, the best results are associated to the lower forecast horizon. With NARX technique the worst value is for H400_UDP, while best value is for H400_TCP.(See Figure 6.3(b)). To a greater value of forecast horizon doesn't corresponds a greater value of MAEN. Performances aren't better than FTDNN case. ARIMA technique produce the the worst value for H100_UDP and the best result is associated to the higher forecast horizon. The greater is the forecast horizon, the greater is MAEN value. In Holt-Winters methods, Better MAEN values are registered for H100_UDP case (See Figure 6.4(a)) and the worst value is for H100_TCP. However performances are somewhat comparable with ARIMA ones.

Examining the Jitter values (from the same 6.6) table, can be observed that with the FTDDNN the best result is associated to the lower forecast horizon (See Figure 6.5(a)). TCP data prediction seems to be better performed than UDP data prediction. The worst case is for H400_UDP. With NARX, the worst value is for H400_UDP. Best value, instead, occur for H100_TCP. Order of magnitude of MAEN is the same that in the case of FTD neural networks. Observing the obtained ARIMA values , the worst value is for H100_UDP. Increasing the forecast horizon the obtained MAEN values are better. The best value is for H400_TCP. Jitter prediction with Holt-Winters produces the worst value is for H400_TCP. While the best value is for H100_TCP (See Figure 6.6(a)). Error values are comparable with ARIMA ones (See Figure 6.6(b)).

An overall view is seen in table 6.2, we can note some interesting characteristics of the prediction performance. In first place, comparing both Neural Networks we can see that FTDNN has better performance. Focusing on Delay parameter is possible to note that there are no substantial differences using different prediction horizon (H = 100 or 400), but the best MAEN , in general, are obtained with H=400. Paying attention on Jitter MAEN values is natural to note that they are lower than which are obtained with Delay (10^{-2}). The most performing techniques are FTDNN (with H=100) and ARIMA (with H=400) for this parameter. For both Delay and Jitter parameters , in general , in case of TCP transport protocol there is a better prediction performance than in UDP case. For the Packet Loss, instead, there are no MAEN values because this QoS parameter is always zero in these two analyzed data packages.

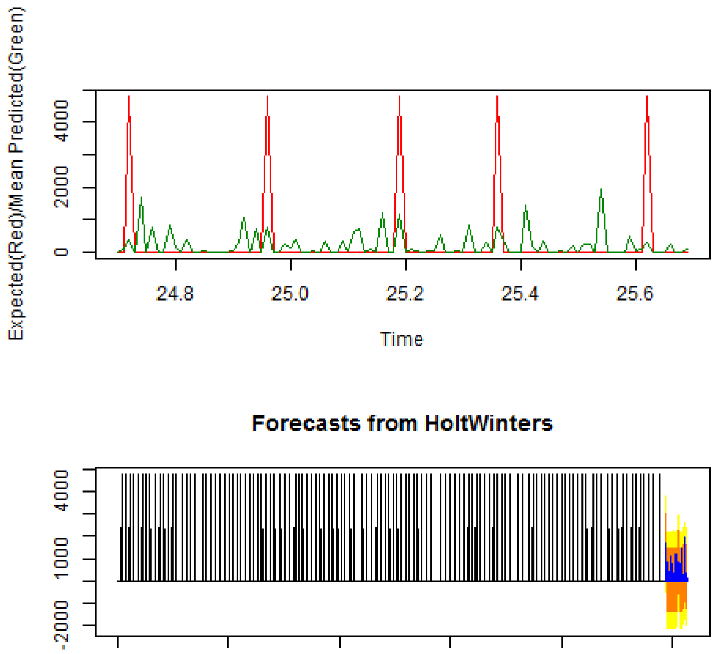


(a) PARAM=Delay, PROT=TCP, TECH=FTDNN, H=100

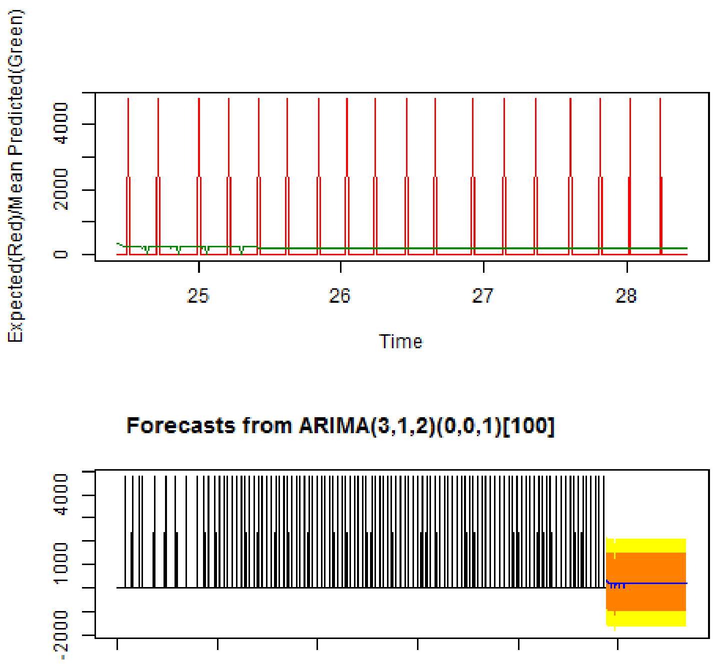


(b) PARAM=Delay, PROT=TCP, TECH=NARX, H=400

Figure 6.3: Prediction plots of Delay with ANN

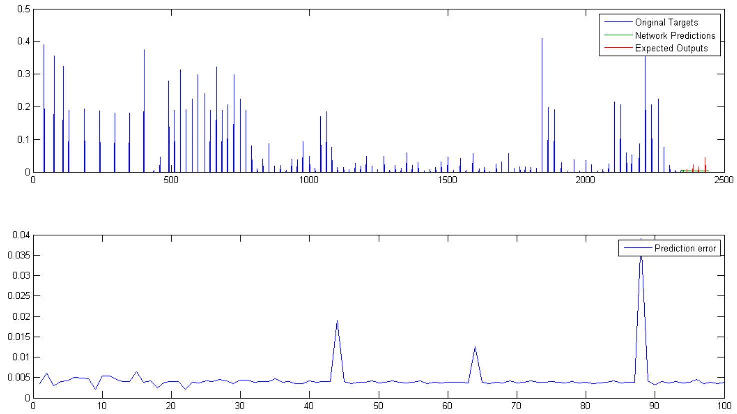


(a) PARAM=Delay, PROT=UDP, TECH=Holt-Winters, H=100

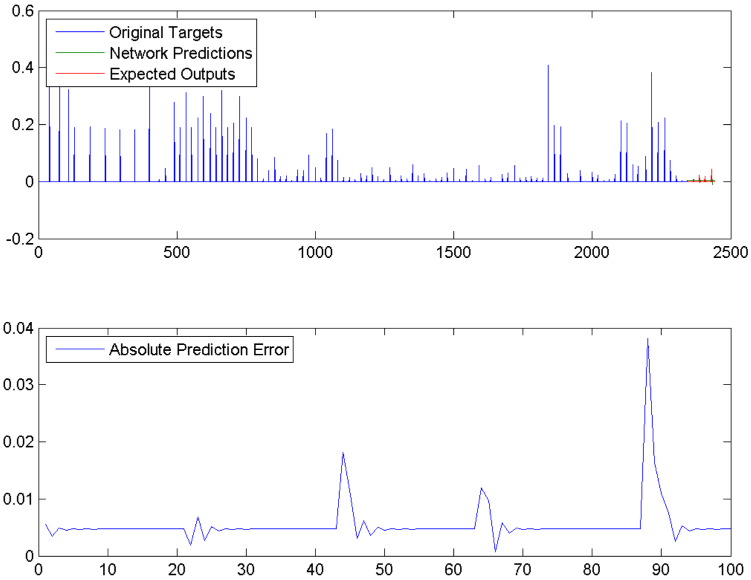


(b) PARAM=Delay, PROT=TCP, TECH=ARIMA, H=400

Figure 6.4: Prediction plots of Delay with Holt-Winters and ARIMA

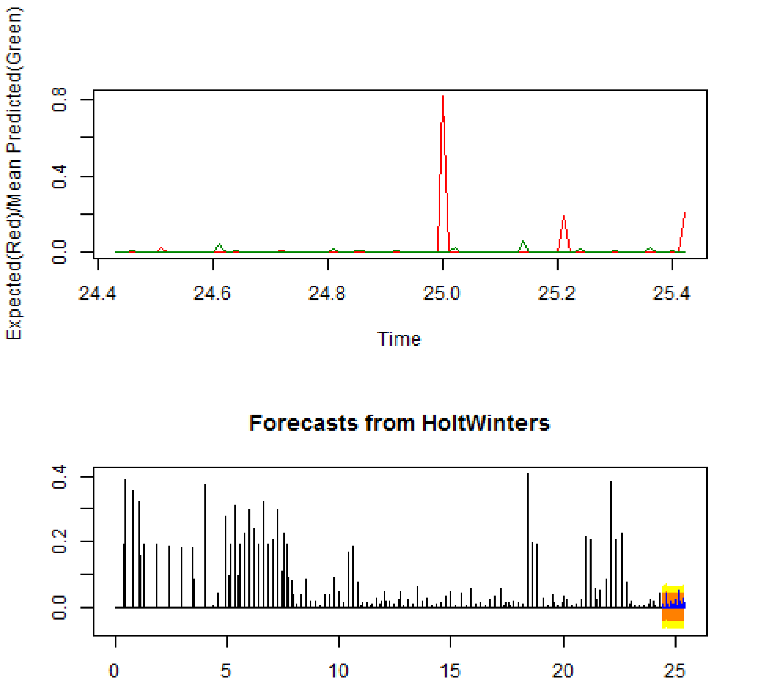


(a) PARAM=Jitter, PROT=TCP, TECH=FTDNN, H=100

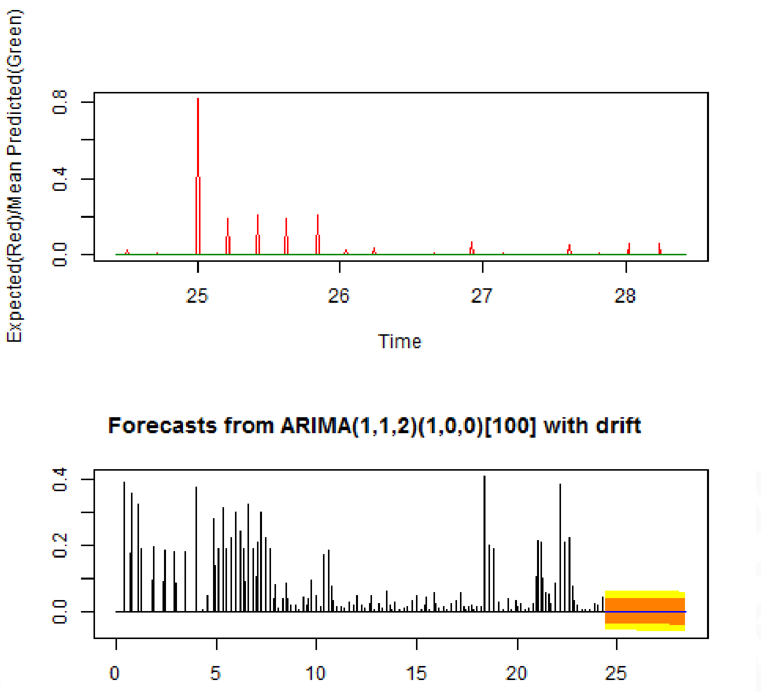


(b) PARAM=Jitter, PROT=TCP, TECH=NARX, H=100

Figure 6.5: Prediction plots of Jitter with ANN



(a) PARAM=Jitter, PROT=TCP, TECH=Holt-Winters, H=100



(b) PARAM=Jitter, PROT=TCP, TECH=ARIMA, H=400

Figure 6.6: Prediction plots of Jitter with Holt-Winters and ARIMA

Table 6.2: GPRS-to-wired trace MAEN Discussion

GPRS-to-wired trace MAEN Discussion									
		FTDNN		NARX		ARIMA		H-W	
		TCP	UDP	TCP	UDP	TCP	UDP	TCP	UDP
Delay	H100	✓							✓
	H400			✓		✓			
Jitter	H100	✓		✓				✓	
	H400					✓			

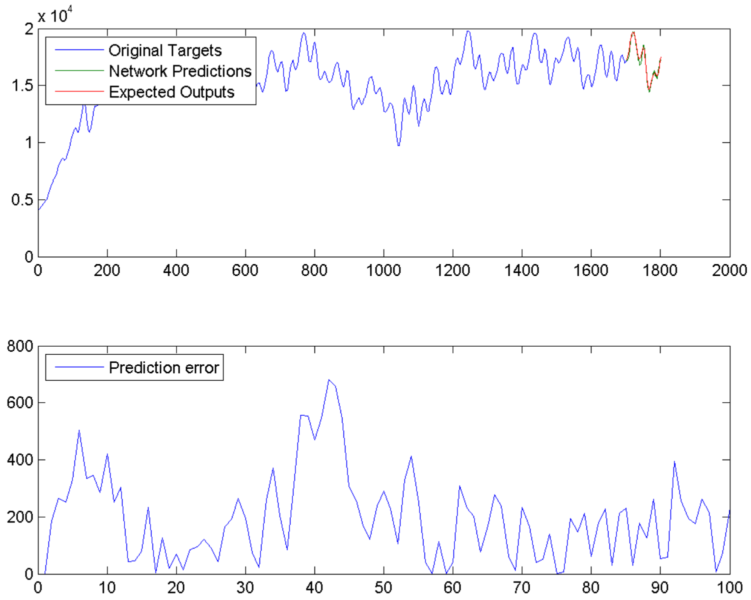
6.2.2 MagNets Network

Regarding the MagNets data traces, following packages are used :

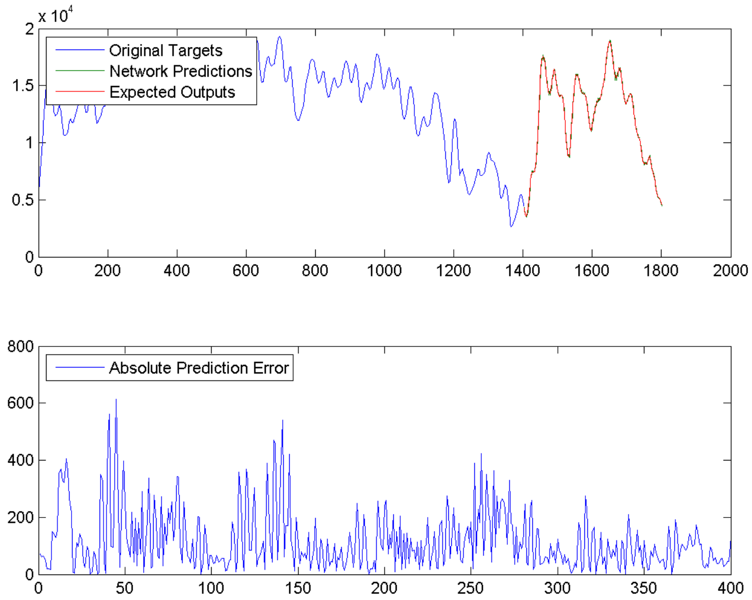
- HHI-TC-11000 TCP and UDP.

As said in the section 6.1.3, the prediction was made for original time series and for each component (Trend and Remainder, Seasonal component was excluded because prediction of seasonal time series is very accurate since the periodicity). Since the periodical nature of seasonal component, and since the duration of time series we're analyzing is few minutes, we ignored considerations about seasonal components and focused on trend and remainder components. The performance results are shown from Table 6.7 to Table 6.13.

Focusing on Table 6.14 and Bitrate parameter, for FTDNN it's possible to see that all best values are for H=100. Prediction of Trend (See Figure 6.7(a)) has a MAEN lower than the original time series and also remainder, except than in case H=400. In fact, in this case MAEN is greater than 1 (worst value of test), that means prediction of FTDNN is not accurate. Original Time series and Remainder component of Time Series have the same order of MAEN. Moreover, TCP results are generally better than UDP results. For NARX techniques (See Figure 6.7(b)), in general, all H=400 prediction cases are well performed. The worst value comes with UDP Reminder and H=100. Best values are registered for Trend TCP/UDP prediction cases. Regarding ARIMA techniques, best performance are in original time series for UDP case (See Figure 6.8(b)) and trend time series for TCP case. Only in original time series and UDP case, increasing the forecast horizon we can see a MAEN 4 times lower. Most cases of best performances are in H100 configurations. Finally for Holt-Winters algorithm, in most cases H100 configurations produces better results. In H400 trend prediction, both tcp and udp produces results greater than 1, that means the procedure has not good performances. In the same Table 6.14, relating to Delay parameter, for FTDNN it's possible to see

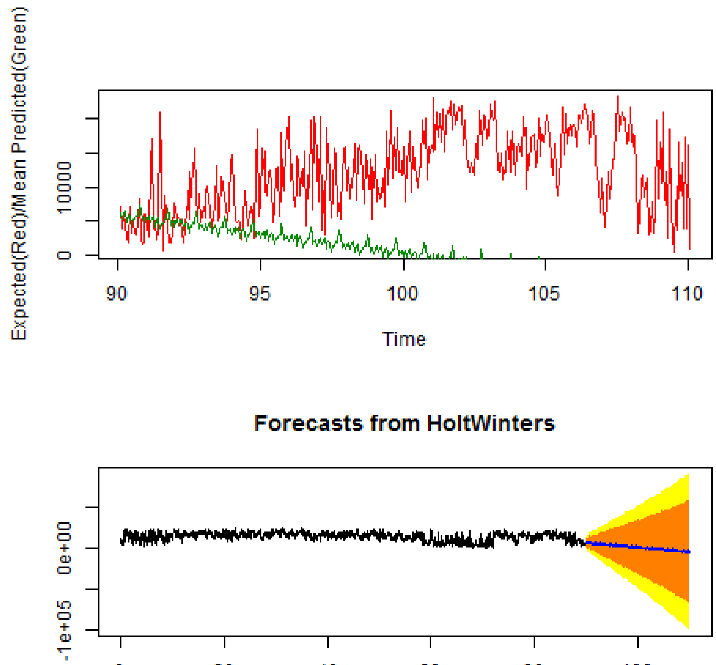


(a) PARAM=Bitrate, COMPONENT=Trend, PROT=TCP, TECH=FTDNN, H=100

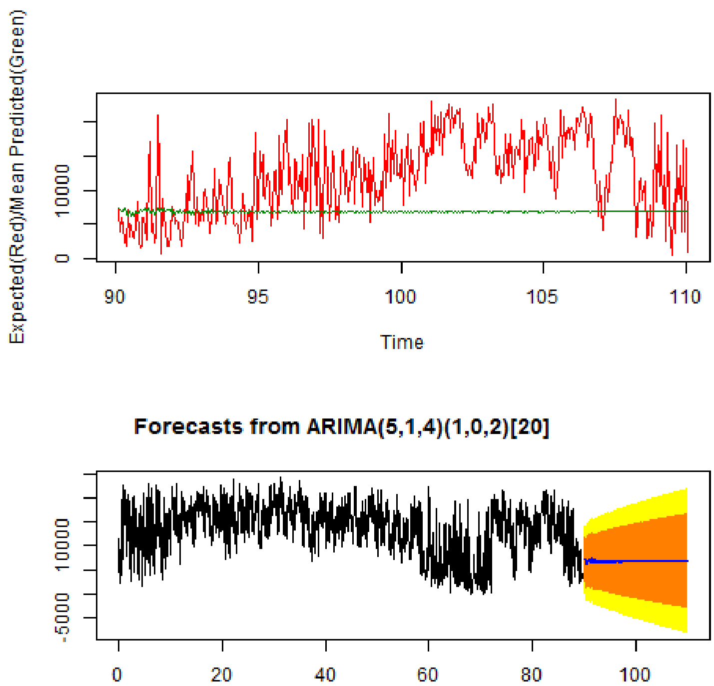


(b) PARAM=Bitrate, COMPONENT=Trend, PROT=UDP, TECH=NARX, H=400

Figure 6.7: Prediction plots of Bitrate with FTDNN and NARX

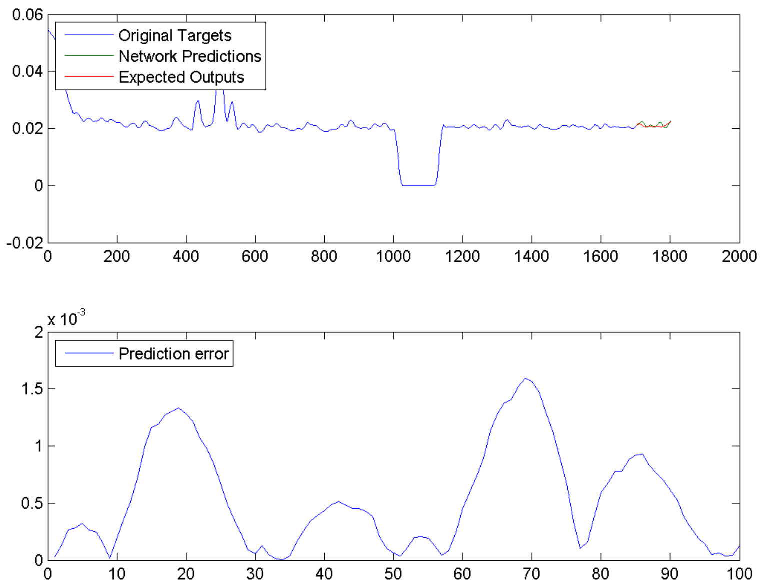


(a) PARAM=Bitrate, COMPONENT=All, PROT=UDP, TECH=HoltWinters, H=400

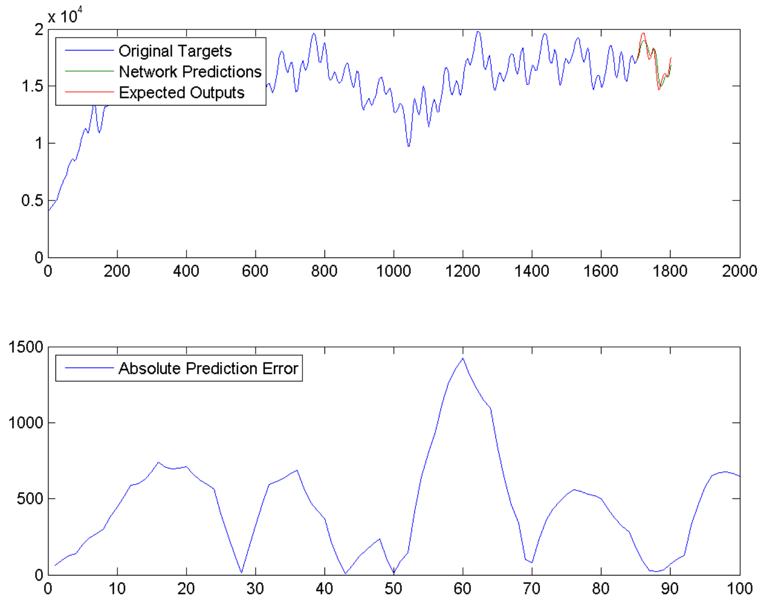


(b) PARAM=Bitrate, COMPONENT=ALL, PROT=UDP, TECH=ARIMA, H=400

Figure 6.8: Prediction plots of Bitrate with Holt-Winters and ARIMA

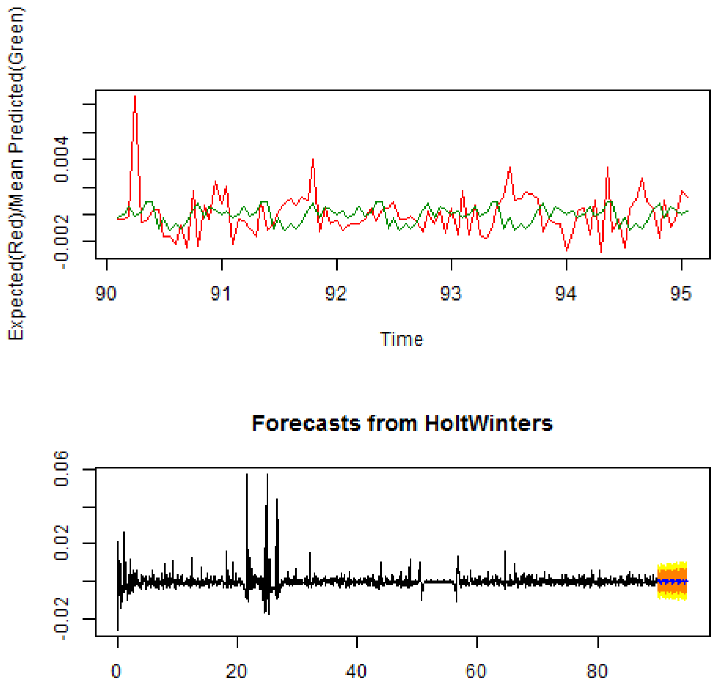


(a) PARAM=Delay, COMPONENT=Trend, PROT=UDP, TECH=FTDNN, H=100

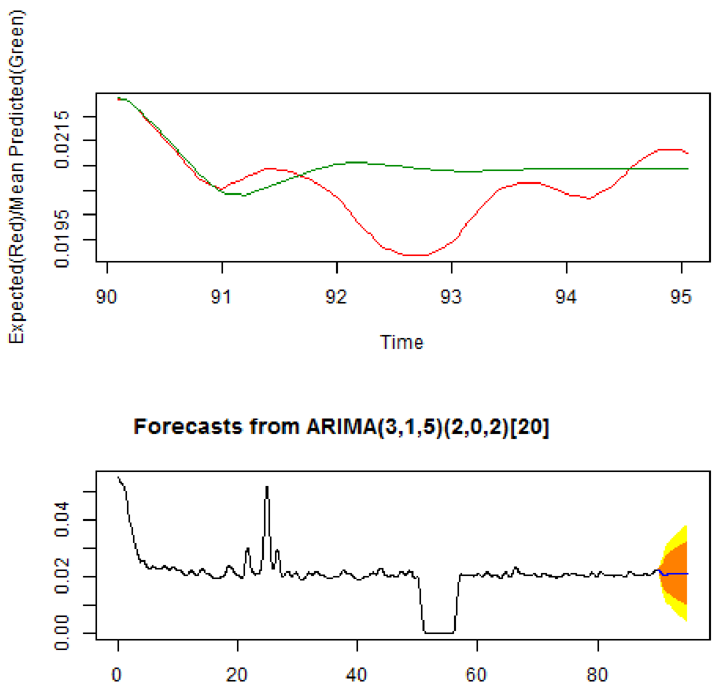


(b) PARAM=Delay, COMPONENT=Trend, PROT=TCP, TECH=NARX, H=100

Figure 6.9: Prediction plots of Delay with FTDNN and NARX



(a) PARAM=Delay, COMPOMPONENT=Remainder, PROT=UDP, TECH=HoltWinters, H=100

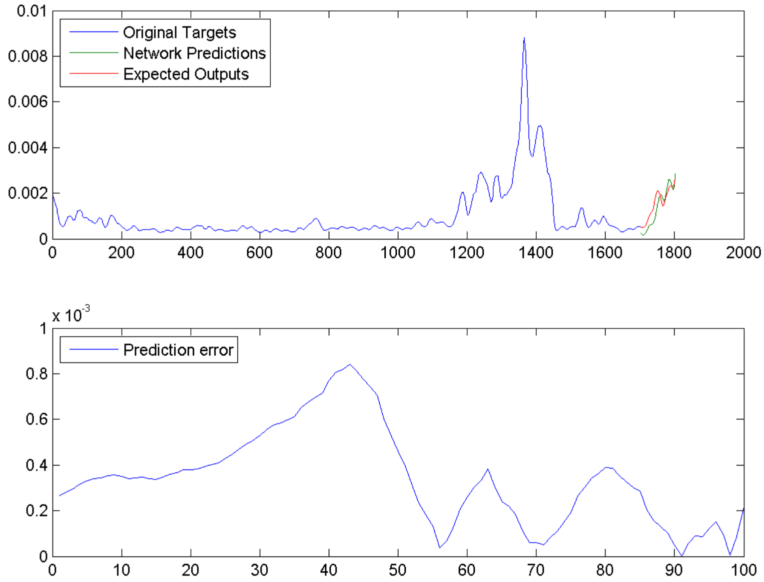


(b) PARAM=Delay, COMPONENT=Trend, PROT=UDP, TECH=ARIMA, H=100

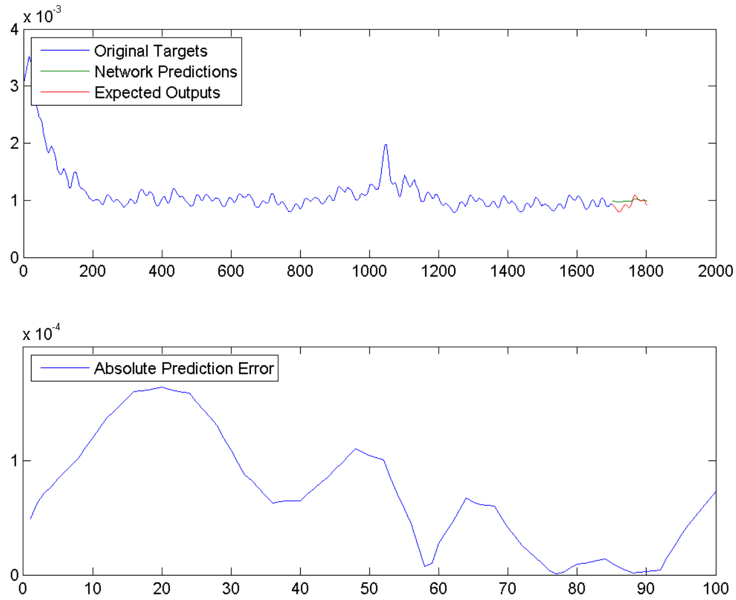
Figure 6.10: Prediction plots of Delay with Holt-Winters and ARIMA

that best performances are in trend prediction (See Figure 6.9(a)), in particular in UDP case. In some cases H400 case has better performance than H100 case, while the worst performance are in TCP Remainder prediction. For TCP data, almost best values occur with horizon 100. In contrast with UDP cases, in which all best MAEN are registered with an horizon of 400 (See Figure 6.9(b)). For ARIMA techniques (See Figure 6.10(b)), all the best performance are in H100 case, except in trend TCP case, in which difference with H100 is not big. In case of TCP remainder and original Time Series, MAEN is greater than one. Error in case H400 is greater than H100. In Holt-Winters algorithm, all best performance are in H100 case. Best result (See Figure 6.10(a)) is in UDP case, for remainder component.

Focusing on Table 6.15 and Jitter parameter, for FTDNN it's possible to see that all best values occur for H=100. Trend prediction performance seems to be the best among the other components and the whole time-series. Note that for H=400 all TCP components provide Normalized MAE values greater than "1", as occur also for UDP Season component. So FTDNN is not accurate for H400 for this parameter. With NARX techniques, best value is for forecast horizon 100, Trend component and TCP protocol (See Figure 6.11(b)). In ARIMA section, some values are greater than "1". Over all the best MAEN values are registered for H=400 in TCP time series and with UDP Reminder component (See Figure 6.12(b)), while for Holt-Winters model the best values occur for H=400. In general we have good values with H=100. In the same Table 6.15, relating to Packet Loss Parameter with UDP transport protocol (in case of TCP, Packet Loss is zero), for FTDNN it's possible to see that MAEN values are better for H=100 (See Figure 6.13(a)). With NARX techniques, the best value is for the Trend component and with H=100 (See Figure 6.13(b)). For all other component performances are in a lower level. Regarding ARIMA models, the best value occurs for Trend component and H=100 (See Figure 6.14(b)). All the other values are 1 or 2 orders greater than the best value, while for Holt-Winters models there are good values with H=100 (See Figure 6.14(a)). For an overall point of view, from the Table 6.14 and Table 6.15 can be argued that, generally, in case of UDP transport protocol there are better prediction performances, except the case of NARX neural networks in which best performances are reached with TCP transport protocol. Prediction on Trend component and remainder component has better performances than original time series, except the case of Bitrate parameter. Forecast horizon H=100 is the best case for almost all the tests. Learning based techniques have better performances in prediction of the trend component. Since trend component is more smoothed than remainder and original time series, we could expect these results. The

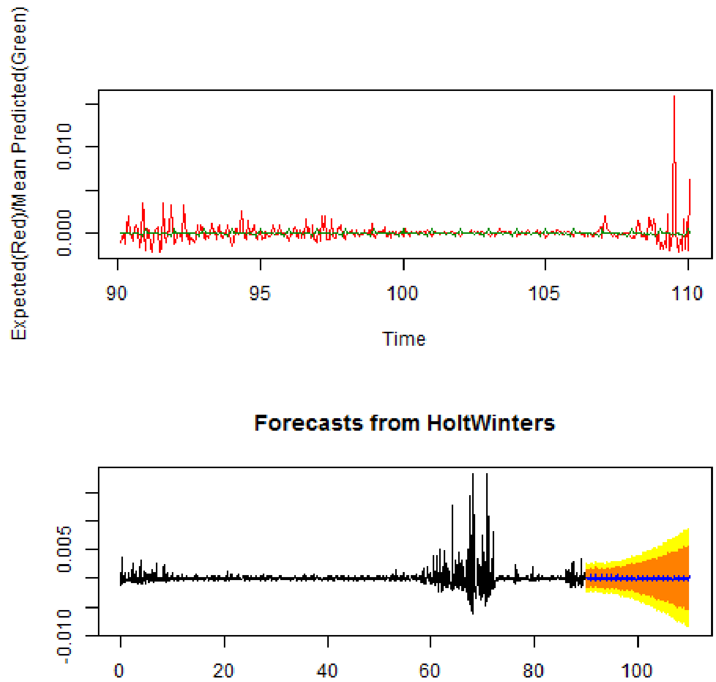


(a) PARAM=Jitter, COMPONENT=Trend, PROT=UDP, TECH=FTDNN, H=100

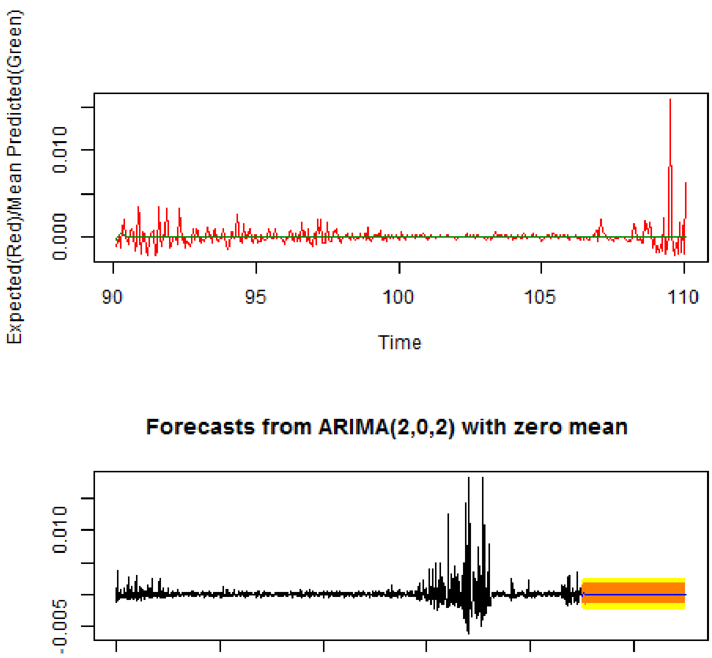


(b) PARAM=Jitter, COMPONENT=Trend, PROT=TCP, TECH=NARX, H=100

Figure 6.11: Prediction plots of Jitter with FTDNN and NARX

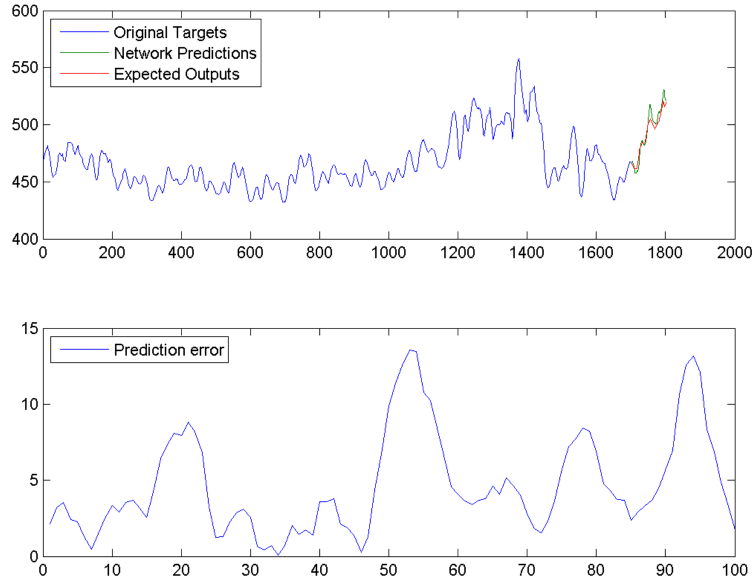


(a) PARAM=Jitter, COMPONENT=Remainder, PROT=UDP, TECH=HoltWinters, H=400

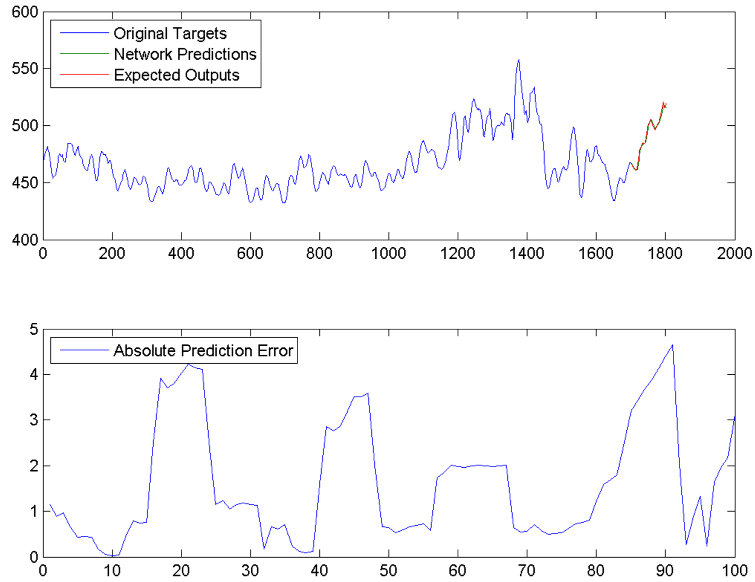


(b) PARAM=Jitter, COMPONENT=Remainder, PROT=UDP, TECH=ARIMA, H=400

Figure 6.12: Prediction plots of Jitter with Holt-Winters and ARIMA

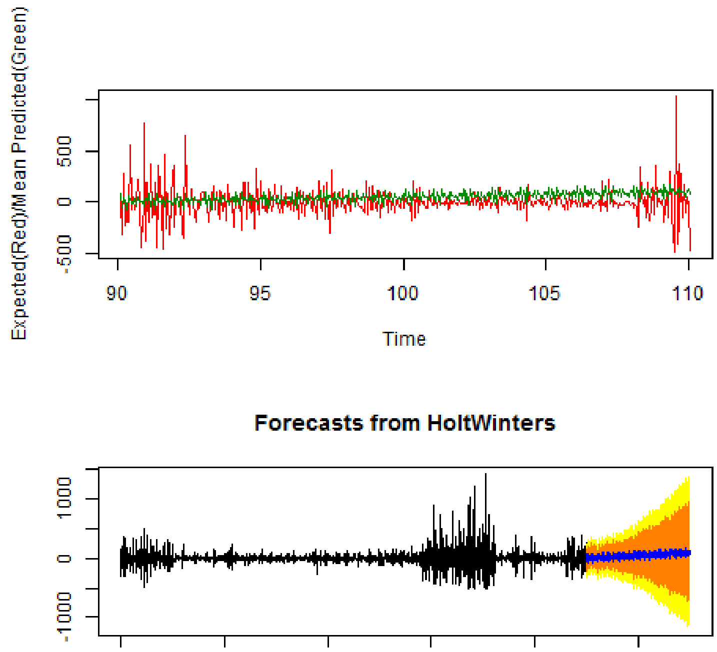


(a) PARAM=Packet Loss, COMPONENT=Trend, PROT=UDP, TECH=FTDNN, H=100

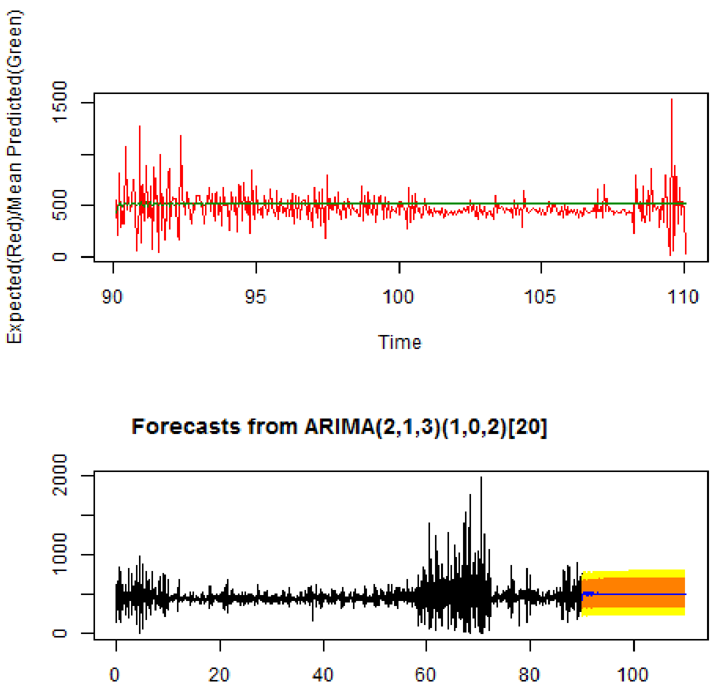


(b) PARAM=Packet Loss, COMPONENT=Trend, PROT=UDP, TECH=NARX, H=100

Figure 6.13: Prediction plots of Packet Loss with FTDNN and NARX



(a) PARAM=Packet Loss, COMPONENT=Remainder, PROT=UDP, TECH=HoltWinters, H=400



(b) PARAM=Packet Loss, COMPONENT=ALL, PROT=UDP, TECH=ARIMA, H=400

Figure 6.14: Prediction plots of Packet Loss with Holt-Winters and ARIMA

Packet Loss parameter is always zero for the TCP protocol, so there aren't related performance values. Table 6.3 gives an overview of the techniques that produce the best MAEN values for each parameter.

Table 6.3: MagNet Short Term best MAEN overview

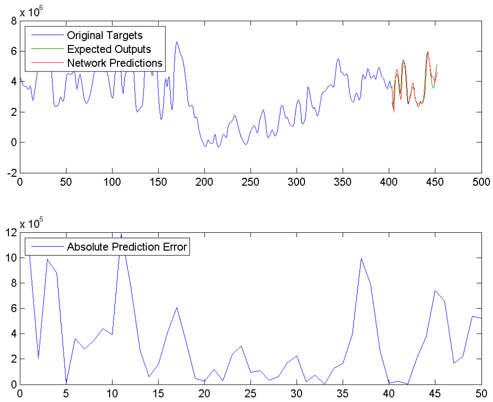
MagNet Short Term MAEN Discussion									
		FTDNN		NARX		ARIMA		H-W	
		TCP	UDP	TCP	UDP	TCP	UDP	TCP	UDP
Bitrate	All	✓					✓		✓
	Trend			✓					
	Remainder								
Delay	All								
	Trend		✓	✓			✓		
	Remainder								✓
Jitter	All								
	Trend		✓	✓		✓			
	Remainder								✓
PacketLoss	All	O		O		O		O	
	Trend	O	✓	O	✓	O	✓	O	
	Remainder	O		O		O		O	✓

6.2.3 SANET Network

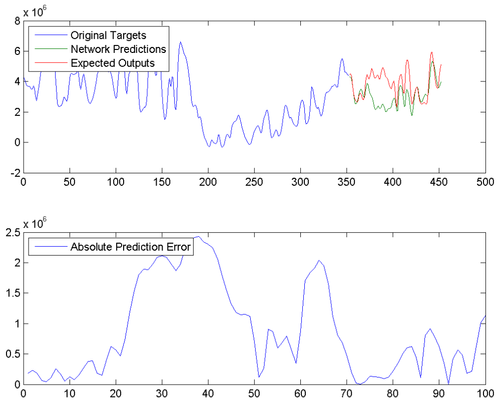
Regarding SANET Network, overall performance with different kinds of errors are showed in Tables 6.16, 6.17, 6.18, 6.19.

As showed in evaluation table 6.20, in Day trace and FTDNN neural networks it's possible to see that the best result is for trend trace and lowest forecast horizon (See figure 6.15(a)). We can expect this result because the trend evolves with small variations and his pattern is generally simpler to predict. Also in NARX case the best results are in prediction of trend trace (See figure 6.15(b)). In case of ARIMA models, performance on trend are lower than ones calculated with neural networks technologies, but the better performance are with remainder with lowest forecast horizon (See figure 6.15(c))

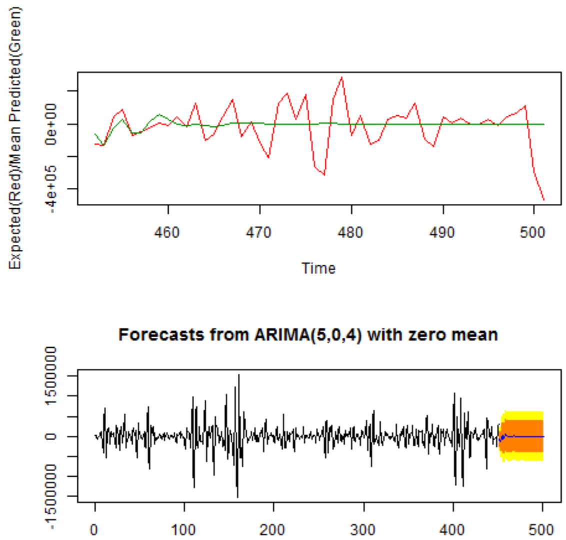
Regarding Week trace in table 6.20 and FTDNN neural networks, best results are with trend and lower forecast horizon (See figure 6.16(a)). Generally increasing of forecast horizon makes a growing of MAEN. FTDNN are the best. Also in NARX case, best results are for trend trace and for lower forecast horizon (See figure 6.16(b)). In case of ARIMA models, prediction on trend trace (that has the best value, as seen in figure 6.16(c)) has the worst results than NARX and FTDNN.



(a) TRACE=Day, H=50, COMP=Trend, TECH=FTDNN

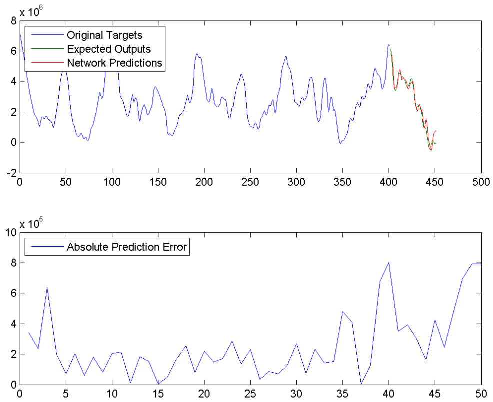


(b) TRACE=Day, H=100, COMP=Trend, TECH=NARX

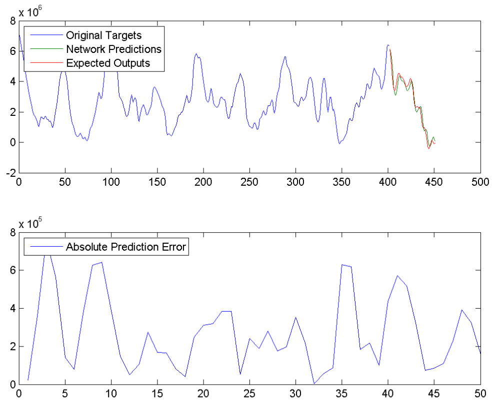


(c) TRACE=Day, H=50, COMP=Remainder, TECH=ARIMA

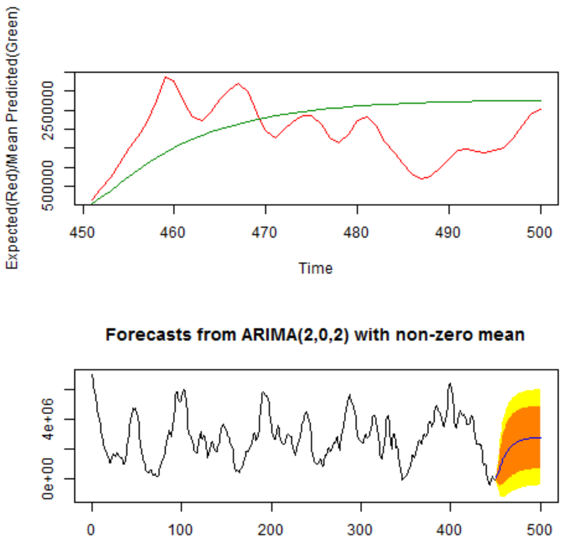
Figure 6.15: Link Load Prediction over a Gigabit Ethernet of COMP component of TRACE dataset with TECH technique and H Horizon



(a) TRACE=Week, H=50, COMP=Trend, TECH=FTDNN



(b) TRACE=Week, H=50, COMP=Trend, TECH=NARX



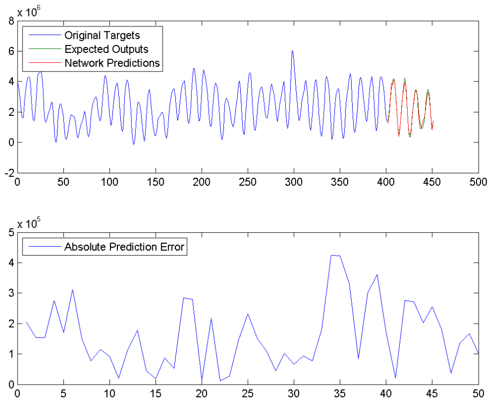
(c) TRACE=Week, H=50, COMP=Trend, TECH=ARIMA

Figure 6.16: Link Load Prediction over a Gigabit Ethernet of COMP component of TRACE dataset with TECH technique and H Horizon

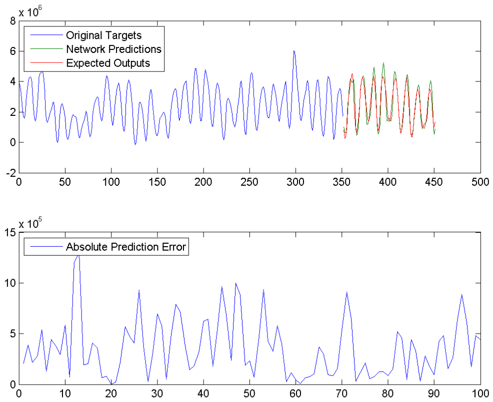
Regarding Month trace in table 6.21, in FTDNN the best values (see figure 6.17(a)) are substantially obtained for H50. The worst value is for Remainder component with H100. Trend component prediction is the best performed. Also in NARX case Trend component prediction shown the best value but this time for H100 (See figure 6.17(b)). The worst value occur for Remainder component with H100. In ARIMA models all the best MAEN values are registered for H50. The relative best value is for Remainder prediction, as seen in figure 6.17(c).

Regarding Year trace in table 6.21, for FTDNN the best values are generally obtained for H50 (See figure 6.18(a)). The worst value is for Remainder component with H100. Trend component prediction is the best performed. Results comparable with the FTDNN ones' obtained for monthly data. In NARX neural networks, the best value is for Trend with H50 (see figure 6.18(b)). However, in general prediction is well performed in case of H100. In ARIMA case, the best value is for the original time series with H50 (see figure 6.18(c)). Comparing these results with FTDNN and NARX we note that Neural Networks perform better than ARIMA.

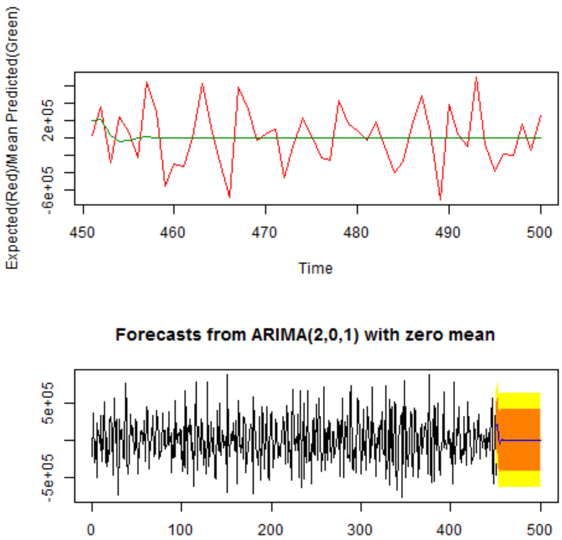
As overall evaluation, as seen in figure 6.4, it is possible to say that FTDNN and NARX neural networks have better performance in trend component prediction. We can expect this result because the trend evolves with small variations and his pattern is generally simpler to predict. In FTDNN case study, better performance are with lower forecast horizon, except the case of seasonal component, in which the best results are reached with higher forecast horizon. It's a good trick to see not only the values of MAEN, but also the way in which the techniques produces a pattern, that follows the real plot of data traces. From this point of view, with Neural Networks results obtained are very accurate, while ARIMA results are not performing well.



(a) TRACE=Month, H=50, COMP=Trend, TECH=FTDNN

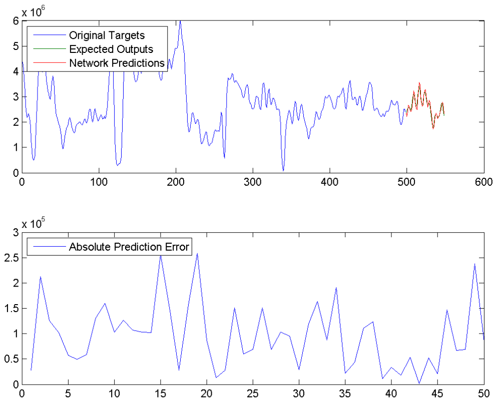


(b) TRACE=Month, H=100, COMP=Trend, TECH=NARX

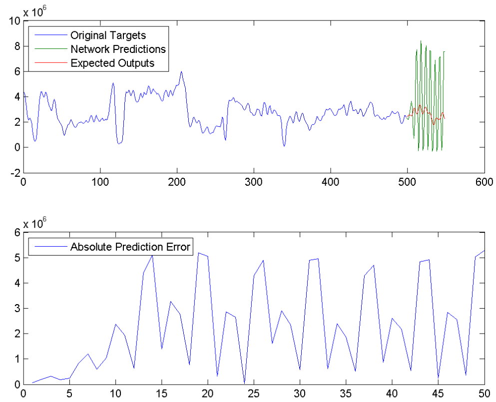


(c) TRACE=Month, H=50, COMP=Remainder, TECH=ARIMA

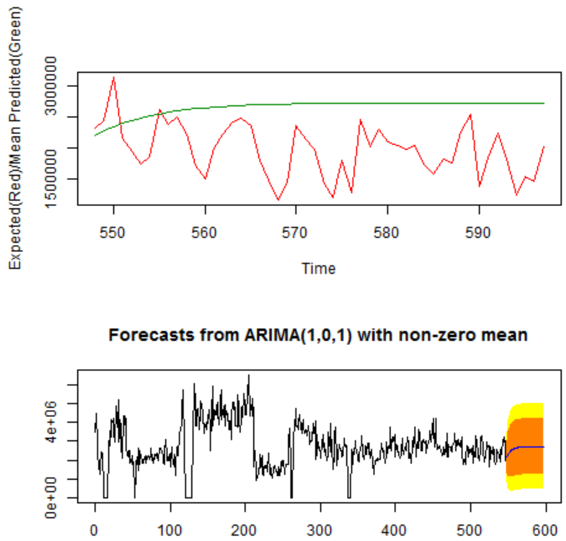
Figure 6.17: Link Load Prediction over a Gigabit Ethernet of COMP component of TRACE dataset with TECH technique and H Horizon



(a) TRACE=Year, H=50, COMP=Trend, TECH=FTDNN



(b) TRACE=Year, H=50, COMP=Trend, TECH=NARX



(c) TRACE=Year, H=50, COMP=ALL, TECH=ARIMA

Figure 6.18: Link Load Prediction over a Gigabit Ethernet of COMP component of TRACE dataset with TECH technique and H Horizon

Table 6.4: SANET Link Load MAEN Discussion

SANET MAEN Discussion				
		FTDNN	NARX	ARIMA
Day	All			
	Season			
	Trend	✓	✓	
	Remainder			✓
Week	All			
	Season			
	Trend	✓	✓	✓
	Remainder			
Month	All			
	Season			
	Trend	✓	✓	
	Remainder			✓
Year	All			✓
	Season			
	Trend	✓	✓	
	Remainder			

6.3 Results and Evaluation tables

In this section, for a better consultation, a list of tables related to the performance metrics is showed.

Table 6.5: GPRS-to-wired-winlin TCP and UDP Error Results

TCP						
Parameter	**Technique**	**Forecast Horizon**	**RMSE**	**MAE**	**MAPE**	**MAEN**
Delay	FTDNN	400	9.64E+02	3.94E+02	6.89E+01	8.19E-02
		100	7.58E+02	3.15E+02	6.08E+01	6.56E-02
	NARX	400	1.00E+03	4.21E+02	9.55E+01	8.75E-02
		100	9.94E+02	5.07E+02	9.43E+01	1.05E-01
	ARIMA	400	9.97E+02	4.12E+02	Inf	8.55E-02
		100	1.05E+03	4.37E+02	Inf	9.09E-02
	Holt-Winters	400	1.01E+03	4.07E+02	Inf	8.46E-02
		100	1.10E+03	4.45E+02	Inf	9.25E-02
Jitter	FTDNN	400	2.96E-02	7.40E-03	9.90E+01	2.27E-04
		100	6.00E-03	4.50E-03	8.71E+01	1.38E-04
	NARX	400	2.96E-02	7.43E-03	9.86E+01	2.28E-04
		100	6.77E-03	5.47E-03	8.44E+01	1.68E-04
	ARIMA	400	4.60E-02	5.68E-03	Inf	1.74E-04
		100	8.67E-02	1.31E-02	Inf	4.01E-04
	Holt-Winters	400	4.66E-02	8.74E-03	Inf	8.74E-03
		100	8.75E-02	1.65E-02	Inf	5.05E-04
PacketLoss	PacketLoss is zero in data trace					
UDP						
Parameter	**Technique**	**Forecast Horizon**	**RMSE**	**MAE**	**MAPE**	**MAEN**
Delay	FTDNN	400	1.00E+03	5.03E+02	9.21E+01	1.04E-01
		100	9.43E+02	4.08E+02	9.50E+01	8.48E-02
	NARX	400	1.15E+03	6.48E+02	9.48E+01	1.35E-01
		100	1.07E+03	4.89E+02	9.53E+01	1.02E-01
	ARIMA	400	1.02E+03	4.44E+02	Inf	9.23E-02
		100	1.05E+03	4.64E+02	Inf	9.64E-02
	Holt-Winters	400	1.07E+03	4.21E+02	Inf	8.74E-02
		100	1.01E+03	3.95E+02	Inf	8.20E-02
Jitter	FTDNN	400	2.41E-01	1.59E-01	1.06E+02	4.82E-03
		100	4.14E-02	2.41E-02	9.04E+01	7.32E-04
	NARX	400	1.72E+00	1.68E+00	2.14E+02	5.10E-02
		100	4.18E-02	1.82E-02	9.58E+01	5.52E-04
	ARIMA	400	1.43E-01	3.01E-02	Inf	9.15E-04
		100	2.75E-01	5.04E-02	Inf	1.53E-03
	Holt-Winters	400	1.45E-01	2.82E-02	Inf	8.55E-04
		100	2.75E-01	4.79E-02	Inf	1.45E-03
PacketLoss	PacketLoss is zero in data trace					

Table 6.6: Results from gprs-to-wired-winlin TCP and UDP Error Evaluation

		Forecast Horizon H	MAEN_TCP	MAEN_UDP
Delay	**FTDNN**	**H100**	6.56E-02	8.48E-02
		H400	8.19E-02	1.04E-01
		Best Value	H100	H100
	NARX	**H100**	1.05E-01	1.02E-01
		H400	8.75E-02	1.35E-01
		Best Value	H400	H100
	ARIMA	**H100**	9.09E-02	9.64E-02
		H400	8.55E-02	9.23E-02
		Best Value	H400	H400
	H-W	**H100**	9.25E-02	8.20E-02
		H400	8.46E-02	8.74E-02
		Best Value	H400	H100
Jitter	**FTDNN**	**H100**	1.38E-04	7.32E-04
		H400	2.27E-04	4.82E-03
		Best Value	H100	H100
	NARX	**H100**	1.68E-04	5.52E-04
		H400	2.28E-04	5.10E-02
		Best Value	H100	H100
	ARIMA	**H100**	4.01E-04	1.53E-03
		H400	1.74E-04	9.15E-04
		Best Value	H400	H400
	H-W	**H100**	5.05E-04	1.45E-03
		H400	8.74E-03	8.55E-04
		Best Value	H100	H400
PacketLoss	PacketLoss is zero in the analyzed time series. MAEN analysis skipped.			

Table 6.7: MagNet Short Term Trace UDP Bitrate Error Results

Magnet Short Term UDP Bitrate Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	100	ALL	4.21E+03	3.26E+03	1.52E+00	1.337E-01
		Seasonal	1.32E-03	1.14E-03	4.00E-06	1.719E-06
		Trend	5.02E+02	3.88E+02	3.82E+00	1.961E-02
		Remainder	3.53E+03	2.68E+03	7.92E+01	1.808E-01
	400	ALL	1.23E+04	9.98E+03	4.28E+01	4.089E-01
		Seasonal	6.07E-04	5.20E-04	6.00E-06	7.814E-07
		Trend	3.64E+04	3.35E+04	2.53E+02	1.696E+00
		Remainder	4.83E+03	3.80E+03	8.14E+01	2.569E-01
NARX	100	ALL	4.20E+03	3.22E+03	9.22E+00	1.318E-01
		Seasonal	3.79E+02	2.98E+02	7.81E+01	4.476E-01
		Trend	5.76E+02	4.66E+02	3.39E+00	2.355E-02
		Remainder	8.15E+03	6.99E+03	8.95E+01	4.718E-01
	400	ALL	3.62E+03	2.85E+03	3.15E+00	1.167E-01
		Seasonal	3.35E+02	2.77E+02	8.71E+01	4.159E-01
		Trend	1.59E+02	1.18E+02	9.55E-03	5.956E-03
		Remainder	3.57E+03	2.80E+03	9.08E+01	1.893E-01
ARIMA	100	ALL	3.91E+03	2.97E+03	6.92E+01	1.216E-01
		Seasonal	error	error	error	
		Trend	8.17E+02	6.22E+02	9.14E+00	3.143E-02
		Remainder	3.52E+03	2.63E+03	1.12E+02	1.774E-01
	400	ALL	7.84E+03	1.39E+01	6.03E+01	5.693E-04
		Seasonal	error	error	error	
		Trend	6.50E+03	5.35E+03	3.76E+01	2.703E-01
		Remainder	3.69E+03	2.94E+03	1.03E+02	1.982E-01
HoltWinters	100	ALL	4.80E+03	3.46E+03	5.82E+01	1.417E-01
		Seasonal	2.58E-14	1.31E-14	7.79E-15	1.967E-17
		Trend	1.31E+04	1.15E+04	1.59E+02	5.813E-01
		Remainder	3.65E+03	2.63E+03	1.94E+02	1.775E-01
	400	ALL	7.16E+02	7.16E+02	1.02E+01	2.933E-02
		Seasonal	3.28E-14	2.13E-14	1.39E-14	3.203E-17
		Trend	4.93E+04	4.34E+04	3.36E+02	2.196E+00
		Remainder	3.81E+03	3.00E+03	1.78E+02	2.029E-01

Table 6.8: Magnet Short Term UDP Delay Error Results

Magnet Short Term UDP Delay Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	100	ALL	5.10E-03	4.20E-03	1.88E+01	3.844E-02
		Seasonal	3.30E-04	2.58E-04	2.21E+01	3.862E-01
		Trend	1.18E-04	9.60E-05	9.72E-02	1.745E-03
		Remainder	1.57E-03	1.19E-03	9.04E+01	2.064E-02
	400	ALL	7.10E-03	5.00E-03	1.18E+00	4.58E-02
		Seasonal	2.83E-04	2.32E-04	1.60E+00	3.47E-01
		Trend	4.64E-03	3.64E-03	1.64E+01	6.61E-02
		Remainder	3.27E-03	2.78E-03	1.07E+02	4.81E-02
NARX	100	ALL	7.06E-02	6.65E-02	3.11E+02	6.084E-01
		Seasonal	3.25E-04	2.68E-04	9.82E+01	4.012E-01
		Trend	3.48E-02	2.54E-02	2.74E+01	4.614E-01
		Remainder	1.65E-03	1.29E-03	1.00E+02	2.243E-02
	400	ALL	2.70E-03	2.08E-03	3.11E+00	1.906E-02
		Seasonal	4.16E-04	3.21E-04	4.78E+01	4.805E-01
		Trend	1.01E-02	1.01E-02	4.89E+01	1.833E-01
		Remainder	1.91E-03	1.41E-03	1.03E+02	2.439E-02
ARIMA	100	ALL	2.33E-03	1.94E-03	9.77E+00	1.779E-02
		Seasonal				
		Trend	7.86E-04	5.59E-04	2.81E+00	1.016E-02
		Remainder	1.58E-03	1.16E-03	1.01E+02	2.016E-02
	400	ALL	5.09E-03	2.82E-03	1.11E+01	2.585E-02
		Seasonal	error	error	error	
		Trend	2.98E-03	1.77E-03	7.02E+00	3.225E-02
		Remainder	4.21E-03	2.37E-03	1.00E+02	4.102E-02
HoltWinters	100	ALL	3.31E-03	2.86E-03	1.45E+01	2.616E-02
		Seasonal	1.19E-19	1.06E-19	7.01E-14	1.583E-16
		Trend	5.28E-03	4.19E-03	2.04E+01	7.623E-02
		Remainder	1.76E-03	1.37E-03	1.48E+02	2.377E-02
	400	ALL	5.17E-03	3.66E-03	1.60E+01	3.354E-02
		Seasonal	4.24E-19	3.71E-19	2.42E-13	5.553E-16
		Trend	2.73E-02	2.29E-02	9.83E+01	4.162E-01
		Remainder	4.25E-03	2.41E-03	1.59E+02	4.184E-02

Table 6.9: Magnet Short Term UDP Jitter Error Results

Magnet Short Term UDP Jitter Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	100	ALL	1.50E-03	1.10E-03	6.13E+01	4.115E-02
		Seasonal	2.62E-04	2.13E-04	1.36E+01	6.677E-01
		Trend	3.28E-04	2.65E-04	9.35E+00	3.011E-02
		Remainder	9.85E-04	7.19E-04	1.01E+02	3.910E-02
	400	ALL	4.90E-03	3.90E-03	4.67E+01	1.46E-01
		Seasonal	3.74E-04	3.52E-04	4.11E+01	1.10E+00
		Trend	3.58E-03	3.08E-03	1.16E+02	3.50E-01
		Remainder	2.89E-03	2.21E-03	9.59E+01	1.20E-01
NARX	100	ALL	2.11E-02	2.04E-02	8.36E+02	7.647E-01
		Seasonal	1.50E-04	1.25E-04	1.03E+02	3.918E-01
		Trend	3.49E-04	3.11E-04	1.84E+01	3.533E-02
		Remainder	9.80E-04	7.18E-04	1.01E+02	3.904E-02
	400	ALL	1.96E-03	1.08E-03	4.58E+01	4.037E-02
		Seasonal	1.55E-04	1.22E-04	1.00E+02	3.824E-01
		Trend	5.02E-03	4.89E-03	2.52E+02	5.559E-01
		Remainder	1.51E-03	6.38E-04	1.03E+02	3.469E-02
ARIMA	100	ALL	1.31E-03	9.94E-04	7.89E+01	3.720E-02
		Seasonal	error	error	error	
		Trend	9.48E-04	7.79E-04	4.87E+01	8.852E-02
		Remainder	1.12E-03	8.13E-04	1.08E+02	4.419E-02
	400	ALL	1.74E-03	1.42E-03	3.09E+02	5.324E-02
		Seasonal	error	error	error	
		Trend	1.87E-03	1.71E-03	2.99E+02	1.945E-01
		Remainder	1.16E-03	5.52E-04	1.02E+02	3.003E-02
HoltWinters	100	ALL	1.40E-03	1.08E-03	8.45E+01	4.035E-02
		Seasonal	1.75E-20	1.34E-20	9.24E-14	4.196E-17
		Trend	5.62E-03	4.79E-03	2.90E+02	5.438E-01
		Remainder	1.18E-03	8.50E-04	1.13E+02	4.621E-02
	400	ALL	2.02E-03	1.71E-03	3.84E+02	6.408E-02
		Seasonal	5.26E-20	4.55E-20	3.22E-13	1.428E-16
		Trend	2.07E-02	1.81E-02	3.02E+03	2.059E+00
		Remainder	1.20E-03	6.03E-04	1.78E+02	3.280E-02

Table 6.10: Magnet Short Term UDP PacketLoss Error Results

Magnet Short Term UDP Packet Loss Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	100	ALL	1.46E+02	1.11E+02	1.55E+01	5.539E-02
		Seasonal	2.70E-05	1.70E-05	2.30E-05	6.468E-07
		Trend	4.11E+00	3.52E+00	1.55E-02	6.301E-03
		Remainder	1.39E+02	1.03E+02	7.99E+01	7.111E-02
	400	ALL	2.58E+02	1.78E+02	5.27E-01	8.916E-02
		Seasonal	3.10E+00	2.04E+00	1.25E+01	7.780E-02
		Trend	2.30E+01	1.90E+01	8.85E-01	3.408E-02
		Remainder	2.41E+02	1.73E+02	1.04E+02	1.196E-01
NARX	100	ALL	1.37E+02	1.03E+02	1.36E+01	5.155E-02
		Seasonal	1.56E+03	1.32E+03	1.31E+03	5.027E+01
		Trend	2.06E+00	1.61E+00	1.97E-01	2.893E-03
		Remainder	1.96E+02	1.51E+02	1.08E+02	1.048E-01
	400	ALL	1.62E+02	9.71E+01	1.06E+01	4.855E-02
		Seasonal	3.95E+01	3.19E+01	5.51E+01	1.215E+00
		Trend	1.52E+02	8.81E+01	9.12E+01	1.578E-01
		Remainder	1.06E+02	1.03E+02	2.19E+01	7.145E-02
ARIMA	100	ALL	2.17E+02	1.60E+02	6.26E+01	7.993E-02
		Seasonal	error	error	error	
		Trend	5.91E+00	4.60E+00	9.01E-01	8.245E-03
		Remainder	2.15E+02	1.59E+02	1.60E+02	1.103E-01
	400	ALL	1.57E+02	1.11E+02	5.71E+01	5.546E-02
		Seasonal				
		Trend	3.99E+01	3.29E+01	7.19E+00	5.899E-02
		Remainder	1.50E+02	9.45E+01	1.15E+02	6.548E-02
HoltWinters	100	ALL	2.28E+02	1.73E+02	7.09E+01	8.679E-02
		Seasonal	4.38E-15	3.94E-15	6.57E-14	1.499E-16
		Trend	1.22E+02	1.05E+02	2.07E+01	1.879E-01
		Remainder	2.20E+02	1.63E+02	1.56E+02	1.129E-01
	400	ALL	3.06E+02	2.66E+02	1.14E+02	1.331E-01
		Seasonal	1.53E-14	1.34E-14	2.33E-13	5.100E-16
		Trend	4.85E+02	4.23E+02	9.12E+01	7.581E-01
		Remainder	1.67E+02	1.22E+02	4.06E+02	8.455E-02

Table 6.11: MagNet Short Term TCP Bitrate Error Results

Magnet Short Term TCP Bitrate Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	100	ALL	1.970E+03	1.572E+03	1.572E+03	6.81E-02
		Seasonal	2.780E-04	2.160E-04	1.900E-05	8.11E-07
		Trend	2.234E+02	1.971E+02	3.388E-01	9.97E-03
		Remainder	1.719E+03	1.370E+03	6.210E+01	1.17E-01
	400	ALL	2.625E+03	2.037E+03	5.376E+00	8.82E-02
		Seasonal	1.257E-03	9.130E-04	1.390E-04	3.43E-06
		Trend	9.537E+02	8.756E+02	5.053E+00	4.43E-02
		Remainder	1.870E+03	1.455E+03	5.543E+01	1.24E-01
NARX	100	ALL	4.006E+03	3.336E+03	1.366E+01	1.44E-01
		Seasonal	3.314E+02	1.901E+02	4.593E+01	7.14E-01
		Trend	5.658E+02	4.613E+02	2.696E-01	2.33E-02
		Remainder	2.501E+03	1.953E+03	8.370E+01	1.67E-01
	400	ALL	2.471E+03	1.975E+03	6.065E+00	8.55E-02
		Seasonal	7.465E+01	6.186E+01	2.166E+01	2.32E-01
		Trend	4.374E+02	3.171E+02	1.052E+00	1.60E-02
		Remainder	2.556E+03	2.149E+03	1.072E+02	1.83E-01
ARIMA	100	ALL	2.907E+03	2.460E+03	1.469E+01	1.06E-01
		Seasonal	error	error	error	
		Trend	1.104E+03	9.679E+02	5.603E+00	4.89E-02
		Remainder	2.338E+03	1.869E+03	9.997E+01	1.60E-01
	400	ALL	2.844E+03	2.433E+03	1.472E+01	1.05E-01
		Seasonal	error	error	error	
		Trend	1.965E+03	1.625E+03	9.872E+00	8.21E-02
		Remainder	2.263E+03	1.856E+03	9.999E+01	1.59E-01
HoltWinters	100	ALL	3.174E+03	2.686E+03	1.640E+01	1.16E-01
		Seasonal	4.798E-14	4.237E-14	1.221E-13	1.59E-16
		Trend	1.098E+04	9.268E+03	5.514E+01	4.69E-01
		Remainder	2.396E+03	1.926E+03	1.131E+02	1.64E-01
	400	ALL	5.061E+03	4.142E+03	2.709E+01	1.79E-01
		Seasonal	1.685E-13	1.475E-13	4.370E-13	5.54E-16
		Trend	4.212E+04	3.651E+04	2.162E+02	1.85E+00
		Remainder	2.370E+03	1.961E+03	1.492E+02	1.67E-01

Table 6.12: MagNet Short Term TCP Delay Error Results

Magnet Short Term TCP Delay Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	100	ALL	1.360E-02	1.100E-02	1.994E+00	2.99E-02
		Seasonal	0.000E+00	0.000E+00	3.170E-04	0.00E+00
		Trend	7.990E-04	6.250E-04	2.350E-01	2.58E-03
		Remainder	5.404E-03	4.254E-03	1.523E+01	3.43E-02
	400	ALL	error	error	error	
		Seasonal	1.034E-03	8.530E-04	8.565E+00	5.60E-01
		Trend	1.646E-02	1.358E-02	1.091E+00	5.60E-02
		Remainder	1.869E-02	1.488E-02	9.356E+01	1.20E-01
NARX	100	ALL	9.788E-03	7.565E-03	2.055E-01	2.06E-02
		Seasonal	1.174E-03	9.980E-04	1.066E+02	6.56E-01
		Trend	5.570E-04	4.100E-04	8.500E-02	1.69E-03
		Remainder	7.892E-03	6.171E-03	3.354E+01	4.97E-02
	400	ALL	1.154E-02	9.298E-03	1.259E-01	2.53E-02
		Seasonal	9.150E-04	7.650E-04	7.974E+01	5.02E-01
		Trend	4.052E-02	3.317E-02	2.376E+00	1.37E-01
		Remainder	1.361E-02	1.021E-02	9.568E+01	8.22E-02
ARIMA	100	ALL	1.812E-02	1.388E-02	6.653E+00	3.77E-02
		Seasonal	error	error	error	
		Trend	1.023E-02	8.113E-03	4.122E+00	3.34E-02
		Remainder	1.316E-02	1.078E-02	1.016E+02	8.68E-02
	400	ALL	2.025E-02	2.248E+00	7.441E+00	6.11E+00
		Seasonal	error	error	error	
		Trend	9.777E-03	7.650E-03	3.804E+00	3.15E-02
		Remainder	1.380E-02	1.004E+02	1.004E+02	8.08E+02
HoltWinters	100	ALL	2.216E-02	1.820E-02	9.168E+00	4.95E-02
		Seasonal	5.30E-20	3.54E-20	6.21E-14	2.33E-17
		Trend	9.550E-03	1.842E+00	3.813E+00	7.59E+00
		Remainder	1.851E-02	1.099E+02	2.456E+02	8.85E+02
	400	ALL	5.871E-02	4.921E-02	2.486E+01	1.34E-01
		Seasonal	1.771E-19	1.510E-19	1.816E-13	9.92E-17
		Trend	1.432E-02	1.143E-02	5.457E+00	4.71E-02
		Remainder	3.440E-02	2.935E-02	5.948E+02	2.36E-01

Table 6.13: MagNet Short Term TCP Jitter Error Results

Magnet Short Term TCP Jitter Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	100	ALL	3.461E-04	2.729E-04	9.207E+00	4.29E-02
		Seasonal	1.000E-06	1.000E-06	2.527E-01	2.19E-02
		Trend	1.300E-05	1.100E-05	5.120E-01	3.12E-03
		Remainder	1.270E-04	9.900E-05	8.157E+01	2.44E-02
	400	ALL	error			
		Seasonal	1.200E-05	1.000E-05	2.041E+01	2.19E-01
		Trend	3.620E-04	3.330E-04	3.477E+01	9.46E-02
		Remainder	4.030E-04	2.970E-04	9.807E+01	7.31E-02
NARX	100	ALL	2.07E-04	1.780E-04	1.012E+01	2.80E-02
		Seasonal	2.20E-05	1.900E-05	1.007E+02	4.16E-01
		Trend	8.70E-05	7.100E-05	5.527E+00	2.02E-02
		Remainder	1.30E-04	1.000E-04	9.164E+01	2.46E-02
	400	ALL	1.94E-04	1.670E-04	8.675E+00	2.62E-02
		Seasonal	2.30E-05	1.900E-05	9.743E+01	4.16E-01
		Trend	1.23E-03	1.195E-03	1.278E+02	3.39E-01
		Remainder	1.59E-04	1.250E-04	1.075E+02	3.08E-02
ARIMA	100	ALL	1.812E-02	1.388E-02	6.653E+00	2.18E+00
		Seasonal				0.00E+00
		Trend	7.160E-05	6.432E-05	6.931E+00	1.83E-02
		Remainder	1.479E-04	1.105E-04	3.302E+02	2.72E-02
	400	ALL	1.816E-04	1.575E-04	1.759E+01	2.47E-02
		Seasonal	error	error	error	
		Trend	1.757E-04	1.485E-04	1.540E+01	4.22E-02
		Remainder	1.438E-04	1.115E-04	1.578E+02	2.74E-02
HoltWinters	100	ALL	2.216E-02	1.820E-02	9.168E+00	2.86E+00
		Seasonal	7.980E-22	2.753E-22	3.810E-15	6.03E-18
		Trend	3.338E-04	2.825E-04	2.968E+01	8.02E-02
		Remainder	1.813E-04	1.417E-04	5.793E+02	3.49E-02
	400	ALL	2.419E-04	2.091E-04	2.422E+01	3.28E-02
		Seasonal	1.026E-21	5.209E-22	5.660E-15	1.14E-17
		Trend	1.268E-03	1.098E-03	1.163E+02	3.12E-01
		Remainder	1.776E-04	1.444E-04	7.270E+02	3.56E-02

Table 6.14: MagNet Short Term Error Evaluation - Bitrate and Delay

MagNet Short Term Error Evaluation – Bitrate (B) and Delay (D)									
	Horizon H	MAEN_TCP				MAEN_UDP			
		ALL	Seas.	Trend	Rem.	ALL	Seas.	Trend	Rem.
FTDNN B	H100	6.81E-2	8.11E-7	9.97E-3	1.17E-1	1.34E-1	1.72E-6	1.96E-2	1.81E-1
	H400	8.82E-2	3.43E-6	4.43E-2	1.24E-1	4.09E-1	7.81E-7	1.70E+0	2.57E-1
	Best	H100	H100	H100	H100	H100	H400	H100	H100
NARX B	H100	1.44E-1	7.14E-1	2.33E-2	1.67E-1	1.32E-1	4.48E-1	2.35E-2	4.72E-1
	H400	8.55E-2	2.32E-1	1.60E-2	1.83E-1	1.17E-1	4.16E-1	5.96E-3	1.89E-1
	Best	H400	H400	H400	H100	H100	H100	H400	H400
ARIMA B	H100	1.06E-1		4.89E-2	1.60E-1	1.22E-1		3.14E-2	1.77E-1
	H400	1.05E-1		8.21E-2	1.59E-1	5.69E-4		2.70E-1	1.98E-1
	Best	H400		H100	H400	H400		H100	H100
H-W B	H100	1.14E-1	1.59E-16	4.69E-1	1.64E-1	1.42E-1	1.97E-17	5.81E-1	1.77E-1
	H400	1.76E-1	5.54E-16	1.85E+0	1.67E-1	2.93E-2	3.20E-17	2.20E+0	2.03E-1
	Best	H100	H100	H100	H100	H400	H100	H100	H100
FTDNN D	H100	2.99E-2		2.58E-3	3.43E-2	3.84E-2	3.86E-1	1.74E-3	2.06E-2
	H400		5.60E-1	5.60E-2	1.20E-1	4.58E-2	3.47E-1	6.61E-2	4.81E-2
	Best			H100	H100	H100	H400	H100	H100
NARX D	H100	2.06E-2	6.56E-1	1.69E-3	4.97E-2	6.08E-1	4.01E-1	4.61E-1	2.24E-2
	H400	2.53E-2	5.02E-1	1.37E-1	8.22E-2	1.91E-2	4.81E-1	1.83E-1	2.44E-2
	Best	H100	H400	H100	H100	H400	H400	H400	H400
ARIMA D	H100	3.77E-2		3.34E-2	8.68E-2	1.78E-2		1.02E-2	2.02E-2
	H400	6.11E+0		3.15E-2	8.08E+2	2.59E-2		3.23E-2	4.10E-2
	Best	H100		H400	H100	H100		H100	H100
H-W D	H100	4.95E-2	2.33E-17	7.59E+0	8.85E+2	2.62E-2	1.58E-16	7.62E-2	2.38E-2
	H400	1.34E-1	9.92E-17	4.71E-2	2.36E-1	3.35E-2	5.55E-16	4.16E-1	4.18E-2
	Best	H100	H100	H400	H400	H100		H100	H100

Table 6.15: MagNet Short Term Error Evaluation - Jitter and Packet Loss

MagNet Short Term Error Evaluation – Jitter (J) and PacketLoss (P)									
	Horizon H	**MAEN_TCP**				**MAEN_UDP**			
		ALL	**Seas.**	**Trend**	**Rem.**	**ALL**	**Seas.**	**Trend**	**Rem.**
FTDNN J	**H100**	4.29E-2	2.19E-2	3.12E-3	2.44E-2	4.12E-2	6.68E-1	3.01E-2	3.91E-2
	H400		2.19E-1	9.46E-2	7.31E-2	1.46E-1	1.10E+0	3.50E-1	1.20E-1
	Best		H100	H100	H100	H100	H100	H100	H100
NARX J	**H100**	2.80E-2	4.16E-1	2.02E-2	2.46E-2	7.65E-1	3.92E-1	3.53E-2	3.90E-2
	H400	2.62E-2	4.16E-1	3.39E-1	3.08E-2	4.04E-2	3.82E-1	5.56E-1	3.47E-2
	Best	H400	H400	H100	H100	H400	H400	H100	H400
ARIMA J	**H100**	2.18E+0	0.00E+0	1.83E-2	2.72E-2	3.72E-2		8.85E-2	4.42E-2
	H400	2.47E-2		4.22E-2	2.74E-2	5.32E-2		1.94E-1	3.00E-2
	Best	H400		H100	H100	H100		H100	H400
H-W J	**H100**	2.86E+0	6.03E-18	8.02E-2	3.49E-2	4.03E-2	4.20E-17	5.44E-1	4.62E-2
	H400	3.28E-2	1.14E-17	3.12E-1	3.56E-2	6.41E-2	1.43E-16	2.06E+0	3.28E-2
	Best	H400	H100	H100	H100	H100	H100	H100	H400
FTDNN P	**H100**	**Packet Loss is zero**				5.54E-2	6.47E-7	6.30E-3	7.11E-2
	H400					8.92E-2	7.78E-2	3.41E-2	1.20E-1
	Best					H100	H100	H100	H100
NARX P	**H100**					5.15E-2	5.03E+1	2.89E-3	1.05E-1
	H400					4.86E-2	1.22E+0	1.58E-1	7.14E-2
	Best					H400	H400	H100	H400
ARIMA P	**H100**					7.99E-2		8.25E-3	1.10E-1
	H400					5.55E-2		5.90E-2	6.55E-2
	Best					H400		H100	H400
H-W P	**H100**					8.68E-2	1.50E-16	1.88E-1	1.13E-1
	H400					1.33E-1	5.10E-16	7.58E-1	8.45E-2
	Best					H100	H100	H100	H400

Table 6.16: SANET Day Trace Error Result

SANET Day Trace Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	50	ALL	1.51E+06	1.03E+06	6.26E+00	2.46E-01
		Seasonal	4.26E+05	3.25E+05	2.47E+01	2.44E-01
		Trend	4.55E+05	3.30E+05	1.55E+00	6.48E-02
		Remainder	4.01E+05	3.10E+05	5.89E+01	4.80E-01
	100	ALL	1.92E+06	1.54E+06	2.52E+01	3.67E-01
		Seasonal	2.39E+05	1.85E+05	7.07E+00	1.38E-01
		Trend	1.13E+06	9.53E+05	1.40E+01	1.87E-01
		Remainder	2.82E+05	2.21E+05	5.30E+01	3.43E-01
NARX	50	ALL	1.54E+06	1.20E+06	2.18E+01	2.85E-01
		Seasonal	7.65E+05	6.07E+05	7.10E+01	4.55E-01
		Trend	2.48E+06	2.08E+06	4.48E+01	4.07E-01
		Remainder	2.85E+05	2.22E+05	4.91E+01	3.43E-01
	100	ALL	1.87E+06	1.31E+06	1.55E+01	3.11E-01
		Seasonal	6.39E+05	4.48E+05	4.08E+01	3.36E-01
		Trend	1.16E+06	8.86E+05	2.16E+01	1.74E-01
		Remainder	2.86E+05	2.20E+05	6.58E+01	3.40E-01
ARIMA	50	ALL	2.52E+06	2.15E+06	6.77E+02	5.11E-01
		Seasonal	7.56E+05	6.50E+05	9.16E+01	4.87E-01
		Trend	3.41E+06	2.86E+06	5.82E+02	5.62E-01
		Remainder	1.35E+05	9.51E+04	1.27E+02	1.47E-01
	100	ALL	3.00E+06	2.78E+06	9.57E+02	6.61E-01
		Seasonal	7.29E+05	6.16E+05	9.50E+01	4.62E-01
		Trend	3.46E+06	3.16E+06	1.14E+03	6.20E-01
		Remainder	1.69E+05	1.13E+05	1.13E+02	1.76E-01

Table 6.17: SANET Week Trace Error Result

SANET Week Trace Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	50	ALL	1.13E+06	9.09E+05	5.61E+00	1.85E-01
		Seasonal	3.76E+05	2.88E+05	4.28E+00	1.29E-01
		Trend	3.33E+05	2.57E+05	5.68E-01	4.81E-02
		Remainder	2.77E+05	2.34E+05	6.21E+01	2.34E-01
	100	ALL	2.40E+06	1.59E+06	5.05E-01	3.24E-01
		Seasonal	3.15E+05	2.46E+05	4.17E+00	1.10E-01
		Trend	8.83E+05	6.97E+05	9.49E-01	1.31E-01
		Remainder	4.48E+05	2.69E+05	1.61E+01	2.69E-01
NARX	50	ALL	9.53E+05	7.57E+05	1.71E-01	1.54E-01
		Seasonal	5.25E+05	4.18E+05	9.27E+00	1.88E-01
		Trend	3.30E+05	2.70E+05	1.76E+00	5.05E-02
		Remainder	2.70E+05	2.23E+05	7.21E+01	2.23E-01
	100	ALL	9.25E+05	7.48E+05	7.32E+00	1.53E-01
		Seasonal	8.50E+05	6.46E+05	5.04E+01	2.91E-01
		Trend	1.39E+06	1.12E+06	3.13E+00	2.09E-01
		Remainder	4.51E+05	3.55E+05	9.52E+01	3.55E-01
ARIMA	50	ALL	1.51E+06	1.21E+06	2.17E+02	2.46E-01
		Seasonal	9.93E+05	8.35E+05	1.42E+02	3.75E-01
		Trend	1.04E+06	8.82E+05	6.15E+01	1.65E-01
		Remainder	2.89E+05	2.21E+05	9.99E+01	2.21E-01
	100	ALL	1.43E+06	1.13E+06	2.00E+02	2.31E-01
		Seasonal	1.31E+06	1.11E+06	1.20E+02	4.97E-01
		Trend	1.64E+06	1.34E+06	3.16E+02	2.52E-01
		Remainder	2.37E+05	1.76E+05	1.00E+02	1.76E-01

Table 6.18: SANET Month Trace Error Result

SANET Month Trace Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	50	ALL	6.49E+05	5.44E+05	6.52E+00	9.17E-02
		Seasonal	3.44E+05	2.78E+05	4.09E+01	1.80E-01
		Trend	1.92E+05	1.60E+05	2.69E+00	3.22E-02
		Remainder	3.13E+05	2.36E+05	5.31E+01	3.33E-01
	100	ALL	8.73E+05	7.08E+05	8.58E-01	1.19E-01
		Seasonal	2.58E+05	2.11E+05	1.51E+01	1.36E-01
		Trend	3.14E+05	2.46E+05	1.52E-02	4.94E-02
		Remainder	4.55E+05	3.73E+05	6.02E+01	5.26E-01
NARX	50	ALL	7.73E+05	5.93E+05	9.52E+00	1.00E-01
		Seasonal	4.54E+05	3.46E+05	8.60E+01	2.24E-01
		Trend	4.53E+05	3.81E+05	2.27E+00	7.65E-02
		Remainder	8.47E+05	7.15E+04	7.35E+01	1.01E-01
	100	ALL	9.70E+05	7.34E+05	7.72E+00	1.24E-01
		Seasonal	6.26E+05	5.07E+05	1.23E+02	3.28E-01
		Trend	4.58E+05	3.58E+05	2.35E+00	7.20E-02
		Remainder	3.03E+05	2.40E+05	9.83E+01	3.39E-01
ARIMA	50	ALL	9.04E+05	7.53E+05	4.33E+01	1.27E-01
		Seasonal	4.62E+05	3.87E+05	1.08E+02	2.50E-01
		Trend	1.06E+06	9.15E+05	4.11E+01	1.84E-01
		Remainder	3.30E+05	8.60E+04	1.11E+02	1.22E-01
	100	ALL	9.98E+05	7.96E+05	4.80E+01	1.34E-01
		Seasonal	5.58E+05	4.39E+05	1.04E+02	2.84E-01
		Trend	1.14E+06	9.75E+05	5.75E+01	1.96E-01
		Remainder	3.23E+05	2.61E+05	1.05E+02	3.69E-01

Table 6.19: SANET Year Trace Error Result

SANET Year Trace Error Results						
Technique	**Forecast Horizon**	**Component**	**RMSE**	**MAE**	**MAPE**	**MAEN**
FTDNN	50	ALL	4.49E+05	3.61E+05	4.07E+00	1.15E-01
		Seasonal	1.66E+05	1.36E+05	1.56E+01	2.42E-01
		Trend	1.16E+05	9.65E+04	1.77E-01	3.83E-02
		Remainder	1.09E+05	8.71E+04	3.81E+01	2.70E-01
	100	ALL	5.67E+05	4.49E+05	7.56E+00	1.43E-01
		Seasonal	1.36E+05	1.12E+05	1.13E+01	1.98E-01
		Trend	1.53E+05	1.28E+05	8.28E-01	5.08E-02
		Remainder	1.34E+05	1.04E+05	4.44E+01	3.24E-01
NARX	50	ALL	9.53E+05	7.57E+05	1.71E-01	2.40E-01
		Seasonal	5.25E+05	4.18E+05	9.27E+00	7.42E-01
		Trend	3.30E+05	2.70E+05	1.76E+00	1.07E-01
		Remainder	2.70E+05	2.23E+05	7.21E+01	6.92E-01
	100	ALL	9.25E+05	7.48E+05	7.32E+00	2.38E-01
		Seasonal	8.50E+05	6.46E+04	5.04E+01	1.15E-01
		Trend	1.39E+06	1.12E+06	3.13E+00	4.43E-01
		Remainder	4.51E+05	3.55E+04	9.52E+01	1.10E-01
ARIMA	50	ALL	8.44E+05	7.35E+05	4.41E+01	2.33E-01
		Seasonal	2.70E+05	2.20E+05	1.43E+02	3.90E-01
		Trend	8.96E+05	8.15E+05	4.92E+01	3.24E-01
		Remainder	1.31E+05	1.05E+05	1.01E+02	3.26E-01
	100	ALL	8.58E+05	7.51E+05	4.47E+01	2.39E-01
		Seasonal	3.02E+05	2.52E+05	1.21E+02	4.47E-01
		Trend	8.12E+05	7.39E+05	4.17E+01	2.94E-01
		Remainder	1.40E+05	1.14E+05	1.00E+02	3.54E-01

Table 6.20: SANET Error Evaluation Day and Week Trace

SANET Error Evaluation		Forecast Horizon H	MAEN			
			ALL	**Season**	**Trend**	**Remainder**
Day	**FTDNN**	**H50**	2.46E-01	2.44E-01	6.48E-02	4.80E-01
		H100	3.67E-01	1.38E-01	1.87E-01	3.43E-01
		Best Value	**H50**	**H100**	**H50**	**H100**
	NARX	**H50**	2.85E-01	4.55E-01	4.07E-01	3.43E-01
		H100	3.11E-01	3.36E-01	1.74E-01	3.40E-01
		Best Value	**H50**	**H100**	**H100**	**H100**
	ARIMA	**H50**	5.11E-01	4.87E-01	5.62E-01	1.47E-01
		H100	6.61E-01	4.62E-01	6.20E-01	1.76E-01
		Best Value	**H50**	H100	**H50**	**H50**
Week	**FTDNN**	**H50**	1.85E-01	1.29E-01	4.81E-02	2.34E-01
		H100	3.24E-01	1.10E-01	1.31E-01	2.69E-01
		Best Value	**H50**	**H100**	**H50**	**H50**
	NARX	**H50**	1.54E-01	1.88E-01	5.05E-02	2.23E-01
		H100	1.53E-01	2.91E-01	2.09E-01	3.55E-01
		Best Value	**H100**	**H50**	**H50**	**H50**
	ARIMA	**H50**	2.46E-01	3.75E-01	1.65E-01	2.21E-01
		H100	2.31E-01	4.97E-01	2.52E-01	1.76E-01
		Best Value	**H100**	**H50**	**H50**	**H100**

Table 6.21: SANET Error Evaluation Month and Year Trace

SANET Error Evaluation		Forecast Horizon H	MAEN			
			ALL	**Season**	**Trend**	**Remainder**
Month	**FTDNN**	**H50**	9.17E-02	1.80E-01	3.22E-02	3.33E-01
		H100	1.19E-01	1.36E-01	4.94E-02	5.26E-01
		Best Value	**H50**	**H100**	**H50**	**H50**
	NARX	**H50**	1.00E-01	2.24E-01	7.65E-02	1.01E-01
		H100	1.24E-01	3.28E-01	7.20E-02	3.39E-01
		Best Value	**H50**	**H50**	**H100**	**H50**
	ARIMA	**H50**	1.27E-01	2.50E-01	1.84E-01	1.22E-01
		H100	1.34E-01	2.84E-01	1.96E-01	3.69E-01
		Best Value	**H50**	**H50**	**H50**	**H50**
Year	**FTDNN**	**H50**	1.15E-01	2.42E-01	3.83E-02	2.70E-01
		H100	1.43E-01	1.98E-01	5.08E-02	3.24E-01
		Best Value	**H50**	**H100**	**H50**	**H50**
	NARX	**H50**	2.40E-01	7.42E-01	1.07E-01	6.92E-01
		H100	2.38E-01	1.15E-01	4.43E-01	1.10E-01
		Best Value	**H100**	**H100**	**H50**	**H100**
	ARIMA	**H50**	2.33E-01	3.90E-01	3.24E-01	3.26E-01
		H100	2.39E-01	4.47E-01	2.94E-01	3.54E-01
		Best Value	**H50**	**H50**	**H100**	**H50**

Chapter 7

Conclusion and Future Works

An analysis of the *state of the art* reveals that the neural network represents the best technology in terms of reliability and prediction accuracy. In fact, in recent years there have been many studies on the various techniques that exploit a prediction based learning approach that outperforms, although not overwhelmingly, the various model-based approaches. In addiction, learning-based methods are also preferred due the fact that they can be trained directly on data with thousands of inputs and without the need of a mathematical model, which is instead necessary in the case of model-based techniques such as ARIMA and its variants. In fact, finding a good model is a very difficult and critical task, since prediction is highly affected by the goodness of the mathematical model. In this study ARIMA models parameters are obtained using auto optimization made by R and computed using maximum likelihood estimation.

The results obtained by the various tests were analyzed and were calculated performance metrics based on square error (RMSE), absolute error (MAE and MAEN) and percentage error (MAPE). In this work, the MAEN was defined as the mean absolute error normalized to the maximum value of the analyzed time series. Regarding the evaluation of the errors and thus performance, the MAEN has been chosen, since, being normalized, allows comparison between different parameters, which may present various data scales, and among various techniques.

Tests performed demonstrate that, in general, the prediction carried out with a lower forecast horizon (ie, H = 100 for Magnets and heterogeneous network configurations, H = 50 in case of SANET) has better performance compared to that performed with higher forecast horizon. The best results for end-to-end Delay parameter are obtained predicting UDP protocol data flows of MagNets network, while for gprs-to-wired dataset best performance occur with TCP protocol data flows.

Generally, best results occur with time series that present at least a minimum of seasonality in their patterns. Looking at the plots, we note that the time series which contain little excursions between successive values, are better predicted. The increase of the irregularity of time series associated to a key network parameter, causes a degradation of prediction performance and so the plots do not follow well the actual pattern of the time series. For these reasons the original time series of each parameter is decomposed in seasonal, trend and remainder components, in order to have a better prediction.

Evaluating the computational side we have that, as we already said before, for the model based techniques the task of greater difficulty is to find a good model which models well the time series, while in the case of artificial neural networks, the most critical part is the training of the network that is time consuming, but this disadvantage is offset by improved prediction performances.

For the jitter parameter, we have that the results are specular to those obtained by the delay. In fact, with gprs-to-wired network configurations we have better performances in the case of TCP protocol data flows.

Regarding SANET link load prediction, results show good prediction performance with lower forecast horizon. In particular, best values in term of MAEN occur in making prediction of the trend component with FTDNN and NARX techniques. In general, also for SANET, we have best performance with techniques based on learning.

In conclusion, the techniques of prediction based on a mathematical model that reflects the actual pattern of the statistical parameters of the network, do not represent a preferable choice compared to techniques based on learning. This is given by the fact that the network traffic has particular characteristics which are badly suited to the modeling by means of standard stochastic models. Their chaotic behavior is characterized by sudden periods of high intensity, makes a rigorous and quantitative mathematical treatment difficult.

A list of possible future works that may integrate this work, can be constituted by:

- parameter tweaking and retraining to fit well
- data preprocessing aimed to remove outliers;
- try to use the online techniques to perform prediction;
- work on an hybrid prediction method;
- design a custom neural network that integrate the feature of both FTDNN and NARX networks;
- develop a technical specification (new or borrowed from other scientific fields).

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