Forecasting the number of technicians required for theData and Advanced Services of Telkom

by

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Abstract

As part of a transformation the company is switching over from matching their workload to their workforce to matching their workforce to their workload; i.e. instead of technicians only working in their assigned areas technicians are now moved around between areas to meet the demand as soon as possible.

To assist the company in moving their technicians between areas they will use a forecasting model. This forecasting model can tell the company where technicians will be needed and arrangements for the transfers can be made in advance.

Four forecasting models where developed for each specified region. These models are Holt-Winter Additive as well as Multiplicative models and Ad Hoc models with one using monthly factors and the other using weekly factors. The four models for each region where compared using the Mean Average Deviation (MAD).

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List of abbreviations

FAMC	Fulfilment and Assurance Management Center
CS	Commodity Services
DAS	Data and Advanced Services
FUL	Fulfilment
ASS	Assurance
FUL NV	Fulfilment Non-Voice
ASS NV	Assurance Non-Voice
KPI	Key Performance Indicator
MAD	Mean Average Deviation

Glossary

Assurance	Fixing faults reported by customers
Fulfilment	Installing new devices or services
Region	Specific areas the country have been divided in by the company

Chapter 1

1.1 Introduction

Telkom is Africa's largest integrated communications company. Telkom started in 1991 as essentially a telephone company. Since then they have expanded to include fixed-line, data and mobile services.

To support their ability to maintain their leadership is South Africa while building a strong footprint on the continent, the company has embarked upon a process renewal, in essence, a complete transformation of the way they focus on serving their customers and creating value for their stakeholders (Telkom 2010).

This project was done in the Fulfilment and Assurance Management Center (FAMC) of Telkom. One of this department's functions is to manage the amount of field technicians available. There are a few factors that determine how many technicians are available to fulfill demand. Technicians like any other employees are not available to work due to different types of leave or training. Some of these factors are manageable and others cannot be controlled, for example training can be scheduled to allow for as many technicians to be available as possible whereas sick leave cannot. It is important to manage the manageable factors so as to ensure that there are enough technicians to fulfill the demand as much as possible.

For this departmentthere is another,important, factor that contributes to the availability of the technicians; the geographic location of the technicians, which is a manageable factor. As the term implies, field technicians are dispatched and work outside, away from Telkom office buildings. Technicians are assigned to a specific area or areas but the demand fluctuates and it is thus important to move the technicians to where the demand is. Since Telkom is providing services country wide, this is proving to be a daunting task as the country is divided into almost 600 areas.

These technicians' activities mainly take place in two core product categories as defined by Telkom, namely Commodity Services and Data and Advanced Services. As the name Fulfilment and Assurance Management Center suggests the department manages the Fulfilment(installations) and Assurance (faults) activities of the company. Fulfilment and Assurance are each broken down into voice and non-voice components. The field technicians are divided accordingly taking into account their acquired skills.

As part of their transformationthe company is switching over from matching their workload to their workforce to matching their workforce to their workload i.e. instead of technicians only working in their assigned area technicians are now moved around between areas to meet the demand in as many areas as possible as soon as possible.To assist the company in moving their technicians around between areas they will use a forecasting model. This forecasting model can tell the company where technicians will be needed and arrangements for the transfers can be made in advance.

This project's focus is on the distribution of the field technicians of the Data and Advanced Service (DAS) department of the company. Four forecasting models where developed for each specified region. These models are Holt-Winter Additive as well as Multiplicative models and Ad Hoc models with one using monthly factors and the other using weekly factors.The four models where compared using their Mean Absolute Deviations (MAD) and an applicable model was selected.

1.2 Problem Statement

Telkom employs about 1200 field technicians in their Data and Advanced Services department.These technicians' work isdivided into two broad categories namely Assurance and Fulfilment as defined in the glossary. Each technician is assigned to a specific geographical area(s). The country is divided intoalmost 600 areas.

Telkom used to match their workload to their workforce. This means that technicians only worked in their assigned area(s) and that the time it took to see to a customer's request depended on the workload in that customer's area, thus the higher the demand in an area the longer it would take to see to a customer's request.

As part of their business improvement objectives to improvecustomer satisfaction and to meet their internal KPI's they are now working on matching their workforce to the workload. This means that technicians are now being moved around between areas so as to see to the demand as soon as possible.

However, moving technicians around between areas is not a simple task. It is subject to some negatively influencing factors namely:

- extra travel time(due to the technicians not being assigned to the area and thus not present in the area as well as the technician not knowing the roads in the new area),
- technicians not knowing the infrastructure of the new area (where the Telkom equipment is located),
- not all technicians take ownership of their work when moved outside their assigned area.

If the company can know how many technicians will be required each day in each areathen technicians can be assigned to more than one area, this will improve travel time since they will now be familiar with all their areas, they will know the infrastructure of all their areas and ownership will improve since they are not working in a new area. Another instance is where technicians will not permanently be assigned to more than one area; still it will contribute to productivity if the technicians can be moved to another area from the beginning of the day.

Knowing theFulfilment(installations) and Assurance (faults) intake and consequently the number of technicians required is also proving to be a difficult task due to the inherent instability of the operating environment. Not only can customers request, cancel and amend jobs unpredictably and the environment itself (seasonal changes and traffic) is also not completely predictable.

Other factors that influence the number of technicians required are:

- demography and infrastructure (property expansions require more technicians for a few years for the new infrastructure and installations; also levels of infrastructure differ over the country)
- job duration(a job may take anything from 10minutes to weeks or months if new infrastructure is required, the duration of consecutive jobs is very volatile)
- service level agreements (some jobs have to be completed within four hours from the request being logged, others have to be completed within either eight or twelve hours in order to avoid penalties)
- job may require more than one technician at a time
- special offers (Telkom makes special offers available to customers or prospective customers from time to time, as more people make use of these special offers more technicians are required)
- Some areas are only Fulfilment areas and some are only Assurance areas
- Fulfilment(installation) or Assurance (faults) may be increasing or declining

New data has to be continuously incorporated to generate valid estimations because of these changing conditions.

1.3 Project Aim

The aim of the project is to assist the company in matching their workforce to their workload. By forecasting the number of technicians required in each region the company can know beforehand how to move their technicians around between areas in order to satisfy the demand as far as possible.

Chapter 2

2.1 Literature Study

To solve the problem of not knowing how many technicians are required, when and where, a model was built to estimate how many technicians are required each day in each defined region. There is a wide variety of possible statistical models that can prove to be suitable to meet the requirements.

2.1.1 Understanding the current environment

A UKbased telecommunications company address similar situation as faced by this project. This company did an extensive review of their entire scheduling system. The scope of this project only pertains to a little part of the UK company endeavour namely the workforce forecast.The complete journal of actions taken is not available for public viewing.

Simply stated, field-workforce scheduling is about sending the right technician to the right customer at the right place at the right time with the right equipment—at any time and in any operationalenvironment.Many factors contribute to the complexity of the problem.First, skill requirements vary immensely. The second factor contributing to the complexity of scheduling is the geographical distribution of the workforce (Lesaint et al. 2000).

The problem is further compounded by the inherent instability of the environment self (weather and traffic). Indeed, much schedule information is uncertain, imprecise, and incomplete. Therefore, any scheduling process must continuously incorporate new data to generate valid work assignments but it must also minimize the impact of these data on the current work schedule (Lesaintet al. 2000).

2.1.2 Forecasting

Forecasting is more of an art than a science.

There is a wide variety of forecasting procedures available and no single method is universally applicable. A procedure must be chosen that is most appropriate for the given set of conditions. Forecasting is essentially a form of extrapolation with all the dangers that it entails (Chatfield, 2004). Forecasting should thus not be taken lightly, every aspect should be considered carefully and chosen methods should be validated properly.

According to Chatfield (2004) forecasting methods may be broadly classified into the following three groups:

(i) Subjective

Forecasts made on a subjective basis is made using judgement, intuition, commercial knowledge and any other relevant information. These methods range widely from bold freehand extrapolation to the Delphi technique, in which a group of forecasters tries to obtain a consensus forecast with controlled feedback of other analysts' predictions and opinions as well as other relevant information. More information can be found in Webby and O'Connor (1996).

(ii) Univariate

Forecasts of a given variable are based on a model fitted only to present and past observations of a given time series, possibly augmented by a simple function of time, such as a global linear trend. This would mean, for example, that univariate forecasts of the future sales of a given product would be based entirely on past sales, and would not take account of other economic factor.

(iii) Multivariate

Forecasts of a given variable depend at least partly on values of one or more additional series, called predictor or explanatory variables. For example sales forecasts may depend on stock/ or on economic indices.

In practice, a forecasting procedure may involve a combination of the above mentioned approaches. Marketing forecasts, for example, are often made by combining statistical predictions with the subjective knowledge and insight of people involved in the market. A more formal type ofcombination is to compute a weighted average of two or more objective forecasts, as this often proves superior on average to the individual forecasts (Chatfield 2004). An approach like this could prove to be very useful in finding a suitable forecast for the Data and Advanced Services of the company since the managers have a lot of subjective knowledge and experience that can refine quantitative methods.

Forecasting methods can also be classified as either an automatic approach (requiring no human intervention) or a non-automatic approach (requiring some subjective input from the forecaster). The latter applies to subjective methods and most multivariate methods. Most univariate methods can be made fully automatic but can also be used in a non-automatic form, and there can be a surprising difference between the results (Chatfield 2004).

According to Chatfield 2004 the choice of method depends on a variety of considerations, including:

- How the forecast is to be used.
- The type of time series and its properties. Some series are very regular and hence ‘very predictable’, but others are not. As always, a time plot of the data is very helpful.
- How many past observationsare available.
- The length of the forecasting horizon.
- The number of series to be forecast and the cost allowed per series.
- Analysts should select a method with which they feel good with and for which relevant computer software is available. They should also consider the possibility of trying more than one method.

Appropriate forecasting for this project is time series forecasting. A common goal of time series analysis is extrapolating past behaviour into the future. The data can be analysed to find a trend and can incorporate the seasonal trend that exists within the company’s business functions (Arsham, H1994).

The forecasting model can be built automatically or non-automatically. Automatic forecasting refers to building the model using software to generate the model where as non-automatic forecasting refers to building the model manually.

There are different forecasting models to consider. The forecasting models generally used are exponential smoothing models, Moving Average models, Auto-Regression models or a combination known as Auto-Regression Moving Average models. The Auto-Regression Moving Average models can also be extended to Auto-Regression Integrated Moving Average models and Seasonal Auto-Regression Integrated Moving Average models.

The following diagram depicts a forecasting system. It shows the steps to be followed from obtaining past data to updating the final forecast. The process is divided into two parts. The first part is to analyse data and select an appropriate model to use followed by the generation and development of the forecast. It shows the flow of all the steps and how one will loop until a model is adequate and the forecast is stable.

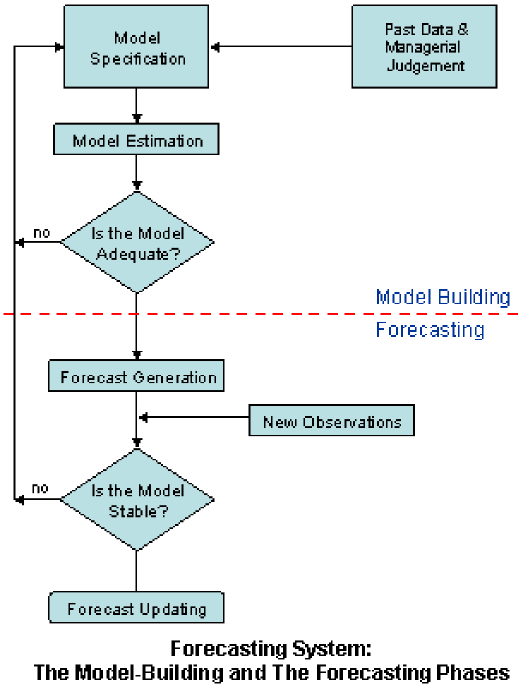


Figure 1: Forecasting System (Arsham, H 1994)

2.1.3 Company structure and current methods

As discussed in the introduction the Fulfilment and AssuranceManagement Center (FAMC)of Telkom has two departments; Commodity Services (CS) and Data and Advance Services (DAS). The diagram below shows the division the Fulfilment and Assurance Management Center down to the level relevant to this project.

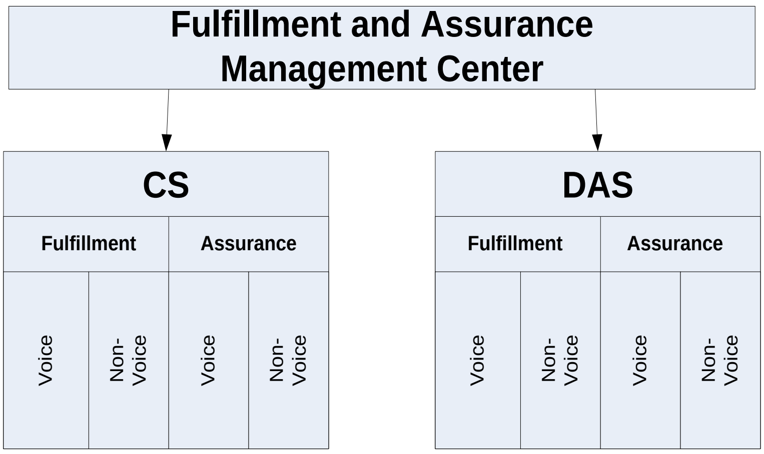


Figure 2: Fulfilment and Assurance Management Center Breakdown

The Fulfilment and Assurance ManagementCentercurrently uses subjective forecasting methods. They translate their experience into a quantified trend to predict the number of technicians required.

2.1.4 Forecasting methods

2.1.4.1 Non-Seasonal Exponential Smoothing

Exponential smoothing is a general class of forecasting procedure that rely on simple updating equations to calculate forecasts. The most basic form is called simple exponential smoothing which should be used for non-seasonal time series showing no systematic trend. If a time series contain a trend or seasonal pattern it can be removed to produce a stationary series (A stationary series is one with no trend or seasonality)(Chatfield, C. 2004). Exponential smoothing can thus be used for many types of time series, for a general review see Gardner 1985.

Given a non-seasonal time series, say $x_1, x_2, \ldots, x_N$, with no systematic trend, it is natural to forecast x_{N+1} by means of a weighted sum of the past observations:

$$\hat{x}_N(1) = c_0 x_N + c_1 x_{N-1} + c_2 x_{N-2} + \ldots \quad (2.1)$$

where the $\{c_i\}$ are weights. It seems sensible to give more weight to recent observations and less weight to observations further in the past. An intuitively appealing set of weights are geometric weights, which decrease by a constant ratio for every unit increase in the lag. In order that the weights sum to one, take

$$c_i = \alpha(1-\alpha)^i i = 0,1$$

whereα is a constant such that $0 < \alpha < 1$. then Equation (5.7) becomes

$$\hat{x}_N(1) = \alpha x_N + \alpha(1-\alpha) x_{N-1} + \alpha(1-\alpha)^2 x_{N-2} + \ldots \quad (2.2)$$

Strictly speaking, Equation (2.2) implies an infinite number of past observations, but in practice there will only be a finite number. Thus Equation (2.2) is customarily rewritten in the recurrence form as

$$\hat{x}_N(1) = \alpha x_N + (1-\alpha)[\alpha x_{N-1} + \alpha(1-\alpha) x_{N-2} + \ldots]$$

$$= \alpha x_N + (1-\alpha)\alpha x_{N-1}(1) \quad (2.3)$$

If one sets$\hat{x}_1(1) = x_1$, then Equation (2.3) can be used recursively to compute forecasts. Equation (5.9) also reduces the amount of arithmetic involved since forecasts can easily be updated using only the latest observation and the previous forecast (Chatfield, C 2004).

The procedure defined by Equation (2.3) is called simple exponential smoothing. The adjective 'exponential' refers to the fact that the geometric weights lie on an exponential curve, but the procedure could equally well have been called geometric smoothing.

Equation (5.9) is sometimes rewritten in the equivalent error-correction form

$$\hat{x}_N(1) = \alpha[x_N - \hat{x}_{N-1}(1)] + \hat{x}_{N-2}(1)$$

$$= \alpha e_N + \hat{x}_{N-1}(1) \quad (2.4)$$

where$e_N = x_N - \hat{x}_{N-1}(1)$ is the prediction error at time N. Equations (2.3) and (2.4) look different at first sight, but give identical forecasts, and it is a matter of practical convenience as to which on should be used.

Although intuitively appealing, it is natural to ask when simple exponential smoothing is a good method to use. It can be shown that simple exponential smoothing is optimal if the underlying model for the time series is given by

$$X_t = \mu + \alpha \sum_{j<t} Z_j + Z_t \quad (2.5)$$

where $\{Z_t\}$ denotes a purely random process. This infinite-order moving average(MA) process is non-stationary, but the first differences $(X_{t+1} - X_t)$ form a stationary first-order MA process. Thus X_t is an autoregressive integrated moving average process of order (0,1,1). In fact it can be shown that there are many other models for which simple exponential smoothing are optimal. This helps to explain why simple exponential smoothing appears to be such a robust method (Chatfield, C 2004).

The value of the smoothing constant α depends on the properties of the given time series. Values between 0.1 and 0.3 are commonly used and produce a forecast that depends on a large number of past observations. Values close to one are used rather less often and give forecasts that depend much more on recent observations. When α = 1, the forecast is equal to the most recent observation.

The value of α may be estimated from past data by a similar procedure to that used for estimating the parameters of an Moving Average process. Given a particular value of α, one-step-ahead prediction errors is computed. This can be repeated for different values of α so that the value, which minimizes the sum of squares, can be found. In more detail, for a given value of α, calculate

$$\hat{x}_1(1) = x_1$$

$$e_2 = x_2 - \hat{x}_1(1)$$

$$\hat{x}_2(1) = \alpha e_2 + \hat{x}_1(1)$$

$$e_3 = x_3 - \hat{x}_2(1)$$

and so on until

$$e_N = x_N - \hat{x}_{N-1}(1) \tag{2.6}$$

and then compute $\sum_{i=2}^{N} e_i^2$. Repeat this procedure for other values of α between0 and 1, say i steps of 0.1, and select the value that minimizes $\sum e_i^2$, either by inspection or using an algorithmic numerical procedure. Modern computers make this all easy to do. Usually the sum of squares surface is quite near the minimum and so the choice of α is not critical (Chatfield, C 2004).

Non-seasonal exponential smoothing is a popular widely used method but for this forecasting effort the seasonal factor cannot be ignored. A non-seasonal forecasting method will thus not be sufficient for this forecasting effort.

2.1.4.2 Seasonal Exponential Smoothing

Exponential smoothing may be generalized to deal with time series containing trend and seasonal variation. The version for handling a trend with non-seasonal data is usually called Holt's (two-parameter) exponential smoothing, while the version that also copes with seasonal variation is usually referred to as the Holt-Winters (three-parameter) procedure. The idea is to generalize the equations for simple exponential smoothing by introducing trend and seasonal terms, which are also updated by exponential smoothing (Chatfield,C 2004).

First the Holt's Exponential Smoothing is considered. In the absence of trend and seasonality, the one-step-ahead forecast from simple exponential smoothing can be thought of as estimate of the local mean level of the series, so that simple exponential smoothing can be regarded as a way of updating the local level of the series, say L_t. This suggests rewriting Equation (2.3) in the form

$$L_t = \alpha x_t + (1 - \alpha)L_{t-1} \tag{2.7}$$

Suppose now wish to include a trend term, T_t say, which is the expected increase or decrease per unit time period in the current level. Then a plausible pair of equations for updating the values of L_t and T_t in recurrence form is the following

$$L_t = \alpha x_t + (1 - \alpha)(L_{t-1} + T_{t-1}) \tag{2.8}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1 - \gamma)T_{t-1} \tag{2.9}$$

Then the h-step-ahead forecast at time t will be of the form

$$\hat{x}_t(h) = (L_t + hT_t) \tag{2.10}$$

For h = 1,2,3,... . There are now two updating equation, involving two smoothing parameters, α and γ, which are generally chosen to lie in the range (0,1).it is natural to call this the two-parameter version of exponential smoothing (Chatfield, C 2004).

The above procedure may readily be generalized to cope with seasonality. Let L_t, T_t, I_t denote the local level, trend and seasonal index, respectively, at time t. The interpretation of I_t depends on whether seasonality is additive or multiplicative. In the former case, $x_t - I_t$ is the deseasonalized value, while in the multiplicative case, it is $\frac{x_t}{I_t}$. The values of the three quantities, L_t, T_t, I_t, all need to be estimated and so there is a need for three updating equations with three smoothing parameters, α, γ, δ. The smoothing parameters range between 0 and 1(Chatfield, C 2004).

The equations for updating L_t, T_t, I_t, when a new observation x_t becomes available, are

$$L_t = \alpha\left(\frac{x_t}{I_{t-s}}\right) + (1 - \alpha)(L_{t-1} + T_{t-1}) \tag{2.11}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1 - \gamma) \tag{2.12}$$

$$I_t = \delta\left(\frac{x_t}{L_t}\right) + (1 - \delta)I_{t-s} \tag{2.13}$$

and the forecasts from time *t* for Additive model is then

$$\hat{x}_t(h) = L_t + hT_t + I_{t-s+h} \tag{2.14}$$

and the forecasts from time *t* for Multiplicative model is then

$$\hat{x}_t(h) = L_t + hT_t + I_{t-s+h} \tag{3.15}$$

According to Chatfield (2004) the following steps should be followed in order to apply Holt-Winter smoothing to seasonal data:

(i) Examine the graph of the data to see whether an additive or a multiplicative seasonal effect is the more appropriate.

(ii) Provide starting values for L_1, and T_1 as wellas seasonal values for the first year, say I_1 , I_2, ..., I_s, using the first few observations in the series in a fairly simple way; for example, the analyst could choose $L_1 = \sum_1^s \frac{x_i}{s}$

(iii) Estimate values for α, γ, δ by minimizing $\sum e_t^2$ over a suitable fitting period for which historical data are available.

(iv) Decide whether to normalize the seasonal indices at regular interval by making them sum to zero in the additive case or have an average of one in the multiplicative case.

(v) Choose between a fully automatic approach (for a large number of series) and a non-automatic approach. The latter allows subjective adjustments for particular series, for example, by allowing the removal of outliers and a careful selection of the appropriate form of seasonality.

Initial values for the model parameters can be estimated as follows (Kalekar, P.S 2004).

Suppose data from *m* seasons are available and let µ denotes the mean of the observations(L = number of seasons).

Estimate of trend component:

$$T_1 = \frac{x_m - \hat{x}_1}{(m-1)L} \tag{3.16}$$

Estimate of level component:

$$L_1 = x_t - \frac{s}{2}T_t \tag{3.17}$$

Estimate of seasonal component:

$$I_1 = \frac{\hat{x}_t}{x_t - [\frac{L+1}{2} - m\,]T_t} \tag{3.18}$$

Exponential smoothing is a procedure for continually revising a forecast in the light of more recent experience. Exponential Smoothing assigns exponentially decreasing weights as the observation get older. In other words, recent observations are given relatively more weight in forecasting than the older observations.

2.1.4.3 Ad Hoc Forecasting

The Ad Hoc forecasting method is a simple forecasting model that can take seasonality into account. Winston, WL (2004) suggests developing the model I the following way:

Use 1 = Monday, 2 = Tuesday, …, 6 = Saturday, 7 = Sunday to denote the days of the week.

Let x_t = number of customers on day t

Forecast:

$$x_t = B \times DW_t \times M_t \times \varepsilon_t \tag{2.19}$$

where

B = base level of customers corresponding to an average day

DW_t = day of the week factor corresponding to the day of the week on which day t falls

M_t = month factor corresponding to the month during which day t occurs

ε_t = random error term whose average value equals 1

To begin estimate B = average number of arrivals per day

$$DW_t \text{for Monday} = \frac{average\ number\ of\ customers}{B} \tag{2.20}$$

Similarly find DW_t for the other days of the week

To estimate M_t

$$M_t \text{for January} = \frac{average\ number\ of\ customers\ on\ January\ day}{B} \tag{2.21}$$

Similarly find M_t for the other months of the year

There is no guarantee that the future will follow the same pattern as the past. This type of model can subjectively be adjusted to give more accurate forecasts. For example if it is observed that the demand is higher on days after a public holiday the model can be adjusted accordingly.

2.1.5 Mean Absolute Deviation (MAD)

The Mean Absolute Deviation is a measure of the performance of a forecasting model. It measures the deviation between a forecasted value and the mean of the series.

$$MAD = \frac{1}{n}\sum_{1}^{n}|\mu - x_i| \tag{2.22}$$

n = Total number of forecasts

x_i = each of the forecasts

μ = mean of the sample values

Chapter 3

3.1 Data Analysis

Since the company operates country wide their work-orders add up to a lot of data entries. Taking this into account together with the fact that the company is growing aMarkovian approach will be followed. On request the company pulled the data of work-orders for the past yearup until the most recent data at the time (November2010 to August2011). In November 2010 the company started to use a new system, data is thus now stored on a different system than before November 2010. This had an impact onacquiring and structuring the data, but after considerable analyses by the company the data was accepted as the best representation obtainable of company activities.

A data set was received in Microsoft Excel® format. This data was then divided into 14 regionsaccording to a manager level defined by the company (each manager is in charge over a set of geographical areas). For the purposes of this project all the geographical areas of the country was divided according to the managers in charge over them. Since one of the regions only contains one geographical area it was left out of the analysis for this project as it can be sufficiently managed.

Different types of company activities require technicians with different skills and because of this the data was broken down further into high level product categories. Each of the regionswere divided into Fulfilment and Assurance activities and then further broken down into voice and non-voice components. This totals to 52 forecasts to be made.

Below is a diagram showing the division discussed above:

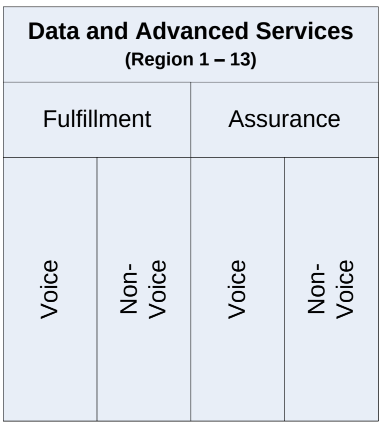


Figure 3: Data and Advanced Services Breakdown

The Assurance (fault) data is based on the date the work-order was created on the system as this translates to the demand for work.

The Fulfilment (installations) data is not based on the date the work-order was created on the system, but on the earliest start date. The earliest start date is the date for which a customer makes an appointment with the company for an installation or the first date when a technician will be available to do the installation.Unfortunately there is no way to distinguish within earliest start date which jobs are done according to appointments and which are done according to the availability of the technicians. There is thus not a pure demand indication, but partially capacity constrained indication of the demand.

Data for the two missing months, September 2010 and October 2010, was obtained by data mining (smoothing) using the Microsoft Excel® add-in XLMiner®.Extreme points in the data were removed to improve the accuracy of the models. Single extreme points and public holidays were replaced by the average of the preceding and succeeding corresponding day of the week; that is if a public holiday fell on a Monday it was replaced by the average of the preceding and succeeding Monday.

The following table describes the column headings used in the data sets:

Entries from original data

Colum title	Explanation
Created Date **or** **WO Early Start Date**	The data the job was created on the system or The earliest the work-order could be started or the date the appointment for the installation was made for
Estimated Duration	A duration determined by work studies (in seconds)
Area Name Description	Telkom name for the area included in the region
Total Time En Route	Total time technicians spent driving to job sites
Total Time On Site	Total time technicians spent on job sites

Table 1: Explanation of data sets' column headings – Original data

Entries from calculated data

Colum title	Explanation
Number of jobs	Number of jobs on a day
Total Time	Total time a technician spent driving to the site and spend on the site for a specific day
Time Tech's Required per Day	Total time all technicians spent driving to sites and spend on sites
Number of Tech's Required	Number of technicians required on a day

Table 2: Explanation of data sets' column headings – Calculated data

The originaldata was used to calculate the data required for analyses to make the forecasts.

Data calculations:

Number of jobs = Count of number of jobs for a specific day (3.1)

Total time = Estimate Duration+Total Time en Route (for all work orders) (3.2)

Time Tech's Required per Day=$[\sum_{1}^{Number\ of\ jobs}(\text{Total Time})]$ (3.3)

Number of Tech's Required = Time Tech's required per Day ÷28800 (3.4)

(28800 = nr of seconds in eight hours since the unit of the data is seconds)

As an example AppendixA shows two data sheets for one of the regions, one of Assurance and the other of Fulfilment. The other datasets can be seen on the included CD.

3.2 Development of Solution

The approach followed is set up according to what the company will be able to repeat with their available or obtainable resources in their available time frame.

3.2.1 Holt-WintersExponential Smoothing

The Holt-Winters Exponential Smoothing models were used since the seasonal component of the data cannot be ignored. Both Additive and Multiplicative models were used for each forecast in order to compare them using the Mean Absolute Deviation (MAD), since the seasonality is neither purely additive or multiplicative.

Since there are 52 forecasts to be made the smoothing parameters (α, β, γ) were determined using subjective estimation and trial and error to test the relation between the parameters to minimize the MAD.Since it takes time to optimize the parameters trial and error was used to find parameters that give low MAD's which are within decimal points of the lowest MAD's for most models. Different parameters were used for the Additive and the Multiplicative models.

The Holt-Winters models were solved automatically using XLMiner®. Sections 3.2.11 and 3.2.1.2 describes the equations used for Holt-Winters models.

3.2.1.1 Additive Model

The following are examples of initial value equations for Holt-Winters models:

$$T_1 = \frac{x_m - \hat{x}_1}{(m-1)L} \tag{3.5}$$

$$L_1 = x_t - \frac{S}{2}T_t \tag{3.6}$$

$$I_1 = \frac{\hat{x}_t}{x_t - [\frac{L+1}{2} - m]T_t} \tag{3.7}$$

Parameter values:

α = 0.15

β = 0.005

δ = 0.005

The following are the equation to update indices for the Additive model:

$$L_t = \alpha\left(\frac{x_t}{I_{t-s}}\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (3.8)$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma) \quad (3.9)$$

$$I_t = \delta\left(\frac{x_t}{L_t}\right) + (1-\delta)I_{t-s} \quad (3.10)$$

$$\hat{x}_t(h) = L_t + hT_t + I_{t-s+h} \quad (3.11)$$

where

L_t = base level estimate

T_t = trend estimate

I_t = seasonal estimate

α = smoothing constant for base level of data

γ = smoothing constant for trend estimate

δ = smoothing constant for seasonality estimate

s = nr of periods in season

h = forecast steps (1,2,3,...s)

x_t = actual value

$\hat{x}_t$ = forecasted value

An example of the results from XLMiner® are presented in Appendix B and the full results can be seen on the included CD.The Mean Absolute Deviations of these models can be seen in section 3.3.

3.2.1.2 Multiplicative Model

The following are examples of initial value equations for Holt-Winters models:

$$T_1 = \frac{x_m - \hat{x}_1}{(m-1)L} \quad (3.12)$$

$$L_1 = x_t - \frac{s}{2}T_t \quad (5.13)$$

$$I_1 = \frac{\hat{x}_t}{x_t - [\frac{L+1}{2} - m]T_t} \quad (3.14)$$

Parameter values:

α = 0.2

β = 0.05

δ = 0.05

The following are the equation to update indices for the Additive model:

$$L_t = \alpha\left(\frac{x_t}{I_{t-s}}\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{3.15}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma) \tag{3.16}$$

$$I_t = \delta\left(\frac{x_t}{L_t}\right) + (1-\delta)I_{t-s} \tag{3.17}$$

$$\hat{x}_t(h) = L_t \times hT_t \times I_{t-s+h} \tag{3.18}$$

where

L_t = base level estimate

T_t = trend estimate

I_t = seasonal estimate

α = smoothing constant for base level of data

γ = smoothing constant for trend estimate

δ = smoothing constant for seasonality estimate

s = nr of periods in season

h = forecast steps (1,2,3,…s)

x_t = actual value

$\hat{x}_t$ = forecasted value

An example of the results from XLMiner® are presented in Appendix C and the full results can be seen on the included CD.

The Mean Absolute Deviations of these models can be seen in section 3.3

3.2.2 Ad Hoc Model

An Ad Hoc model was considered since it can be managed in a non-automatic manner which can be subjectively adjusted to obtain better results. Section 2.1.4.3 describes the Ad Hoc model.

The Ad Hoc forecasting equation is:

$$x_t = B \times D_t \times M_k \times \varepsilon_t \tag{3.19}$$

where

x_t = number of technicians required on day t

B = base level corresponding to the average number of technicians required on a day

D_t = day of the week factor corresponding to the day of the week on which day t falls

M_j = month factor corresponding to the month during which day t occurs

ε_t = random error term whose average value equals 1

t = 1,2 ,3,4,5 (1 = Monday, 2 = Tuesday, 3 = Wednesday, 4 = Thursday, 5 = Friday)

k = 1,2,3,….,12 (1 = January, 2 = February,…., 12 = December)

The Assurance data for Region 1 is used to illustrate this model. The same procedure is followed for the other 51 data sets.

The base level:

B = average number of technicians per day

= 5972.1/261

= 22.88

The day factor for Monday:

D_1 = (average number of arrivals on Monday)/B

= 25.88/22.88

= 1.13

Similarly,

Tuesday: D_2 = 1.04

Wednesday: D_3 = 1.02

Thursday: D_4 = 0.93

Friday: D_5 = 0.87

The month factor for January:

M_1 = (average number of technicians on day in January)/B

= 35.47/22.88

= 1.55

Similarly,

February:	M_2	= 1.24	August:	M_8	= 0.73
March:	M_3	= 1.12	September:	M_9	= 0.87
April:	M_4	= 0.88	October:	M_{10}	= 0.04
May:	M_5	= 0.93	November:	M_{11}	= 1.07
June:	M_6	= 0.91	December:	M_{12}	= 0.95
July:	M_7	= 0.90			

The model above assumes there is only one level per month. To accommodate months where the level fluctuates from week to week this model was adjusted to use weekly factors.

To allow for this equation (3.17) was adjusted to be based on a weekly factor:

$$x_t = B \times D_t \times W_i \times \varepsilon_t \tag{3.20}$$

And the weekly factor was calculated as follows:

W_i = (average number of technicians on day in Week i)/B

where

W_i = week factor corresponding to the week during which day t occurs

i = 1,2,3,….,52 (1 = Week 1, 2 = Week 2,…., 52 = Week 52)

Again the Assurance data for Region 1 is used to illustrate the model. The same procedure is followed for the other 51 data sets.

The base level:

B = average number of technicians per day

= 5972.1/261

= 22.88

The day factor for Monday:

D_1 = (average number of arrivals on Monday)/B

= 25.88/22.88

= 1.13

Similarly,

Tuesday: = 1.04

Wednesday: = 1.02

Thursday: = 0.93

Friday: = 0.87

The week factor for Week 1:

W_1 = (average number of technicians on day in Week 1)/B

= 22.68/22.88

= 1.55

Similarly,

Week 2:	W_2	= 1.55	Week 19:	W_{19}	= 0.87	Week 36:	W_{36}	= 0.76
Week 3:	W_3	= 1.43	Week 20:	W_{20}	= 0.87	Week 37:	W_{37}	= 1.00
Week 4:	W_4	= 1.41	Week 21:	W_{21}	= 0.87	Week 38:	W_{38}	= 1.00
Week 5:	W_5	= 1.34	Week 22:	W_{22}	= 1.00	Week 39:	W_{39}	= 0.92
Week 6:	W_6	= 1.30	Week 23:	W_{23}	= 1.01	Week 40:	W_{40}	= 0.76
Week 7:	W_7	= 1.29	Week 24:	W_{24}	= 0.98	Week 41:	W_{41}	= 0.85
Week 8:	W_8	= 1.09	Week 25:	W_{25}	= 0.76	Week 42:	W_{42}	= 1.03
Week 9:	W_9	= 1.10	Week 26:	W_{26}	= 0.85	Week 43:	W_{43}	= 0.94
Week 10:	W_{10}	= 1.05	Week 27:	W_{27}	= 1.01	Week 44:	W_{44}	= 1.19
Week 11:	W_{11}	= 0.96	Week 28:	W_{28}	= 0.92	Week 45:	W_{45}	= 1.17
Week 12:	W_{12}	= 1.21	Week 29:	W_{29}	= 0.94	Week 46:	W_{46}	= 1.04
Week 13:	W_{13}	= 1.30	Week 30:	W_{30}	= 0.81	Week 47:	W_{47}	= 0.94
Week 14:	W_{14}	= 1.30	Week 31:	W_{31}	= 0.69	Week 48:	W_{48}	= 1.04
Week 15:	W_{15}	= 0.76	Week 32:	W_{32}	= 0.80	Week 49:	W_{49}	= 1.15
Week 16:	W_{16}	= 0.41	Week 33:	W_{33}	= 0.69	Week 50:	W_{50}	= 0.66
Week 17:	W_{17}	= 0.96	Week 34:	W_{34}	= 0.80	Week 51:	W_{51}	= 0.47
Week 18:	W_{18}	= 0.98	Week 35:	W_{35}	= 0.53	Week 52:	W_{52}	= 1.41

An example of the Microsoft Excel®Ad Hoc spreadsheets can be seen in Appendix D and the complete collection can be seen on the included CD.

3.3 Results

The following table shows the Mean Absolute Deviation (MAD) of each of the models for each of the defined regions.

The lowest Mean Absolute Deviation for each model is highlighted.

			Mean Average Deviation (MAD)			
			Additive	Multiplicative	Ad Hoc Month	Ad Hoc Week
Regions	01	ASS	5.94	5.84	3.95	5.10
		FUL	5.12	5.21	2.63	3.42
		ASS NV	2.39	2.43	1.29	1.68
		FUL NV	1.13	1.15	1.49	1.63
	02	ASS	5.60	5.64	7.04	7.57
		FUL	4.85	4.99	2.06	3.04
		ASS NV	2.78	2.66	3.96	4.11
		FUL NV	0.97	1.04	2.50	2.58
	03	ASS	5.66	5.43	3.63	4.46
		FUL	4.67	4.78	1.83	2.84
		ASS NV	2.45	2.49	0.91	1.20
		FUL NV	0.66	0.68	0.63	0.71
	04	ASS	3.39	3.37	2.58	3.44
		FUL	4.15	4.24	1.03	2.42
		ASS NV	3.75	3.86	1.49	1.73
		FUL NV	0.71	0.78	0.78	0.97
	05	ASS	3.54	3.56	1.72	2.35
		FUL	3.62	3.68	1.79	2.52
		ASS NV	1.39	1.44	0.53	0.80
		FUL NV	0.90	1.18	0.94	1.16
	06	ASS	7.15	6.95	8.25	9.29
		FUL	5.88	5.83	2.40	3.63
		ASS NV	1.97	2.02	1.04	1.73
		FUL NV	1.05	1.06	0.74	0.83
	07	ASS	6.56	6.44	6.36	7.25
		FUL	5.18	5.17	3.02	3.54
		ASS NV	3.12	3.14	1.50	2.27
		FUL NV	1.50	1.53	1.00	1.16
	08	ASS	5.88	5.49	7.03	6.04
		FUL	5.12	5.01	3.23	3.32
		ASS NV	1.05	2.51	1.20	1.82
		FUL NV	1.05	1.08	0.51	0.70
	09	ASS	9.88	9.32	8.84	10.94
		FUL	6.58	6.66	2.80	3.73
		ASS NV	4.07	4.08	1.95	2.64
		FUL NV	1.49	1.53	0.96	1.04

			Mean Average Deviation (MAD)			
			Additive	Multiplicative	Ad Hoc Month	Ad Hoc Week
Regions	**10**	**ASS**	8.73	8.51	8.51	11.34
		FUL	6.93	6.69	3.69	4.70
		ASS NV	2.37	2.39	1.19	1.65
		FUL NV	1.92	1.93	1.87	2.03
	11	**ASS**	7.47	6.97	6.54	8.11
		FUL	8.58	8.38	3.86	5.02
		ASS NV	3.87	3.83	1.88	2.72
		FUL NV	1.48	1.55	0.78	1.07
	12	**ASS**	6.90	6.79	6.91	9.20
		FUL	6.42	6.33	2.45	3.76
		ASS NV	1.22	1.24	0.46	0.62
		FUL NV	1.57	1.60	1.22	1.37
	13	**ASS**	14.44	3.68	9.59	11.70
		FUL	4.39	1.45	2.03	2.78
		ASS NV	1.48	4.51	1.00	1.15
		FUL NV	3.57	14.19	1.73	2.17
Nr of lowest MAD's			6	7	39	0

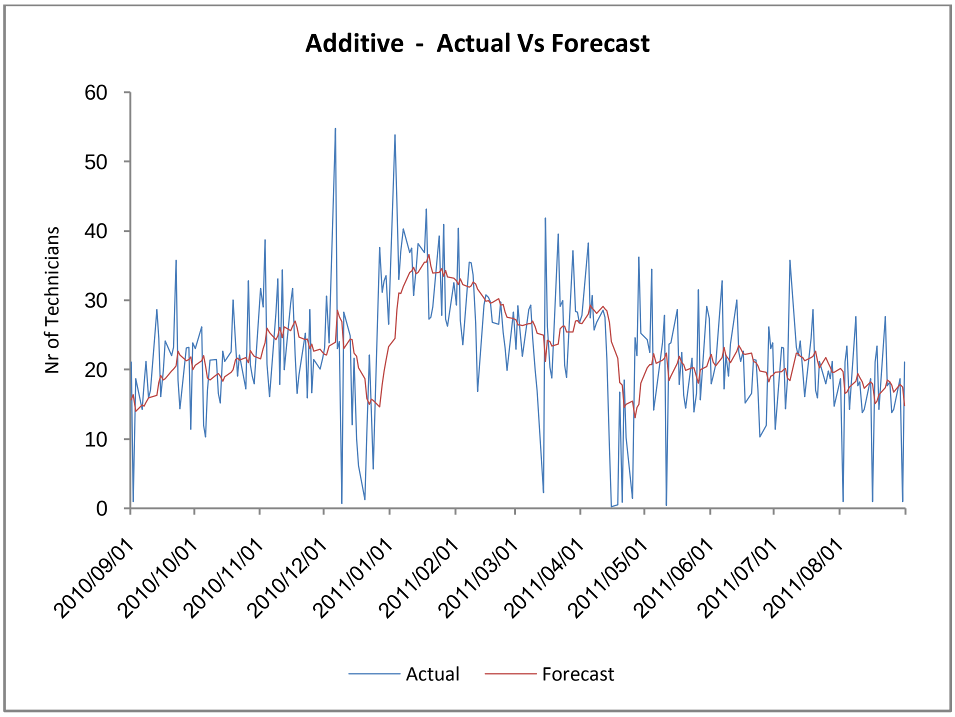
Table 3: Mean Absolute Deviation's from all models

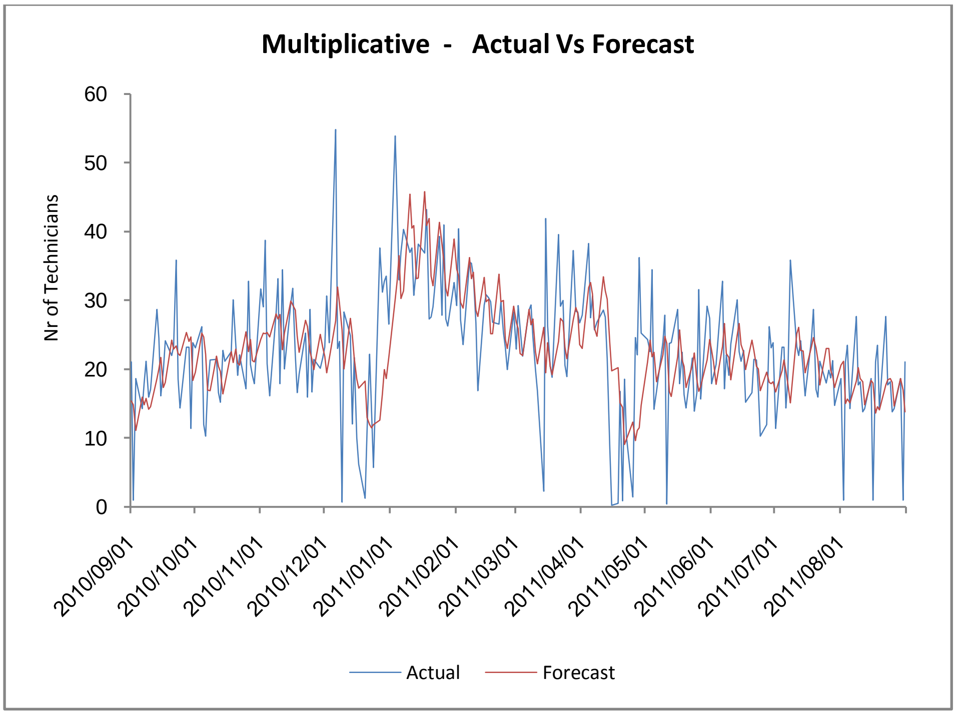
As can be seen from the table above Ad Hoc models performedthe best. Where the Ad Hoc models performed better they performed rather better whereas where the Holt-Winter models performed better they only performed slightly better. Thus where the Holt-Winter models are close to optimal there is a big change that the Ad Hoc could still outperform it.

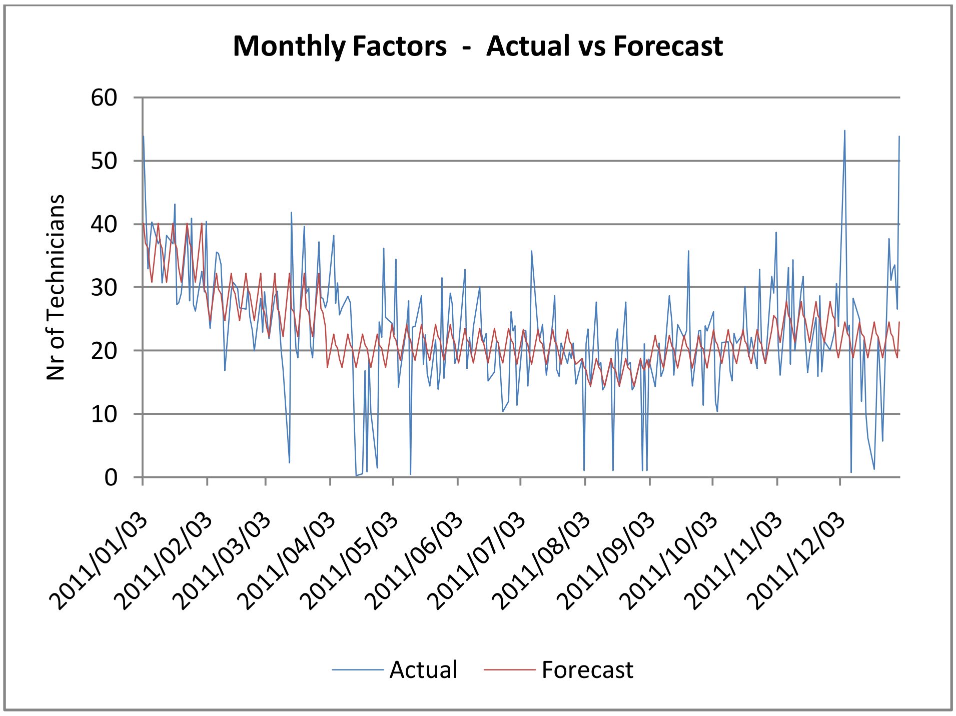
It is in general difficult to make daily and long term forecasts. Holt-Winters models will be able to perform better if more past data is used in the analyses. If the optimization of the smoothing parameters together with the forecasts can be done automatically it might prove to be a useful way to forecast the number of technicians required. To find out more about optimizing the smoothing parameters text like Rasmussen, R (2003) can be consulted.

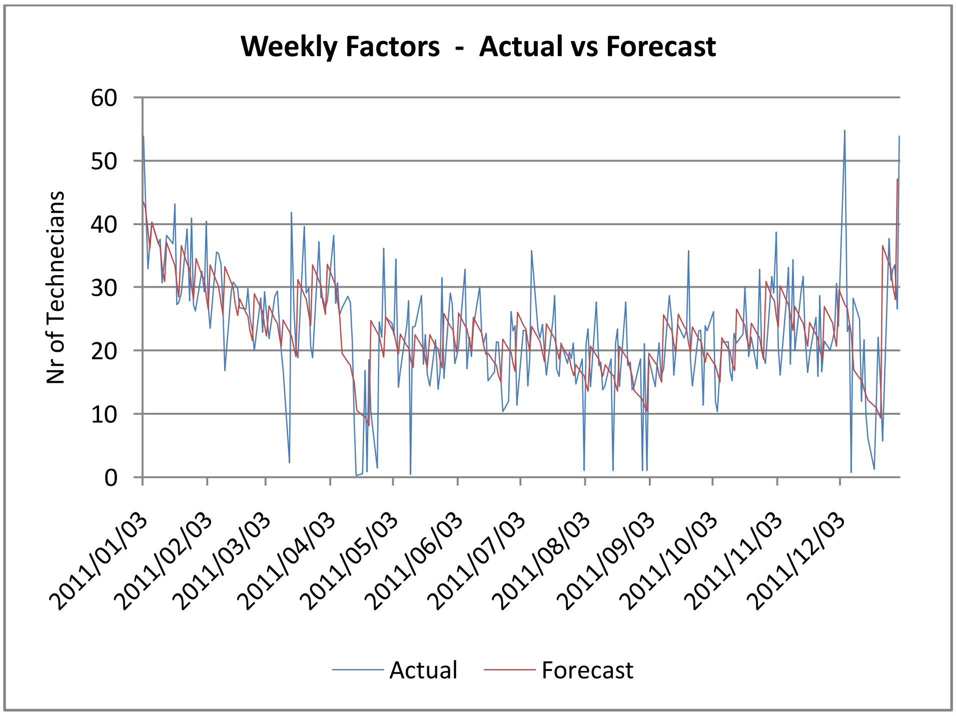
A can be seen from the results the Ad Hoc models using weekly factor consistently performed worse than the Ad Hoc models using monthly factors. This is because the Mean Absolute Deviation measures the deviation from the mean and the models using weekly factors deviate further from the mean since it follows the yearly pattern more closely.

The following two pages show the graphs for Region one Assurance models. All graphs can be seen on the included CD.


Additive - Actual Vs Forecast
Nr of Technicians
60
50
40
30
20
10
0
2010/09/01
2010/10/01
2010/11/01
2010/12/01
2011/01/01
2011/02/01
2011/03/01
2011/04/01
2011/05/01
2011/06/01
2011/07/01
2011/08/01
Actual
Forecast


Multiplicative - Actual Vs Forecast
Nr of Technicians
60
50
40
30
20
10
0
2010/09/01
2010/10/01
2010/11/01
2010/12/01
2011/01/01
2011/02/01
2011/03/01
2011/04/01
2011/05/01
2011/06/01
2011/07/01
2011/08/01
Actual
Forecast


Monthly Factors - Actual vs Forecast
Nr of Technicians
0
10
20
30
40
50
60
2011/01/03
2011/02/03
2011/03/03
2011/04/03
2011/05/03
2011/06/03
2011/07/03
2011/08/03
2011/09/03
2011/10/03
2011/11/03
2011/12/03
Actual
Forecast


Weekly Factors - Actual vs Forecast
Nr of Technecians
0
10
20
30
40
50
60
2011/01/03
2011/02/03
2011/03/03
2011/04/03
2011/05/03
2011/06/03
2011/07/03
2011/08/03
2011/09/03
2011/10/03
2011/11/03
2011/12/03
Actual
Forecast

Chapter 4

4.1 Conclusions and Recommendations

To assist the company in moving their technicians between regions forecasting models were developed. These forecasting models can tell the company where their technicians will be required and arrangements for the transfers between regions can be made in advance.

The company can also use these forecasts for long term planning. For example if a region shows permanent overstaffing, the company can permanently assign the technicians to regions that show permanent or close to permanent under staffing.

Past data was analyzed and forecasting models were built. The results based on the available data were analyzed and it was concluded that the forecasts of how many technicians will be required on a regional levelare to be made withAd Hoc models. According to the results the forecasts are to be made with Ad Hoc models using monthly factors.

If completely automated Holt-Winters models can prove to be useful.It is however recommended that the company should use a model type that can be influenced subjectively. It is thus recommended that the company test the Ad Hoc models for implementation.

4.2 References

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Appendix A -Examples of Datasets

Dataset for region 1 - Assurance

Dataset for region 1 - Fulfilment

Data - Region 1 - Assurance

CREATED_DATE	ESTIMATED_DURATION (Seconds)	AREA_NAME_DESC	TOTAL_TIME_EN_ROUTE (Seconds)	TOTAL_TIME_ON_SITE (Seconds)	Total Time (Seconds)	Number of jobs	Time tech's required per day (Seconds)	Number of Tech's required
2010/09/07	7200	GC-VSTAVEL-BF_ASS-Mere	0	8	7200	5	43097	1.49642361
2010/09/29	7200	GC-VSTAVEL-BF_ASS-Mere	12083	57	19283	3	31705	1.10086806
2010/10/26	7200	GC-VSTAVEL-BF_ASS-Mere	6732	85	13932	18	136621	4.74378472
2010/10/28	7200	GC-VSTAVEL-BF_ASS-Mere	1	12	7201	4	28804	1.00013889
2010/11/02	5400	GC-STEYNWJ-BF_ASS-Krug	2203	4676	7603	1	7603	0.26399306
2010/11/03	5400	GC-VSTAVEL-BF_ASS Auck	7178	8446	12578	2	31246	1.08493056
2010/11/04	5400	GC-MHLANGF-BF_ASS-Joh	2	82	5402	28	223196	7.74986111
2010/11/05	5400	GC-MHLANGF-BF_ASS-Joh	3	6081	5403	60	481410	16.715625
2010/11/06	5400	GC-MHLONGMT-BF_ASS-R	4276	3320	9676	7	134963	4.68621528
2010/11/08	5400	GC-STEYNWJ-BF_ASS-Krug	4893	123	10293	111	913259	31.7103819
2010/11/09	3600	GC-MHLANGF-BF_ASS-Joh	4	12506	3604	118	837943	29.0952431
2010/11/10	5400	GC-VSTAVEL-BF_ASS-Mere	1228	6087	6628	145	1116700	38.7743056
2010/11/11	5400	GC-MHLONGMT-BF_ASS-L	10531	86	15931	87	600576	20.8533333
2010/11/12	5400	GC-STEYNWJ-BF_ASS-Krug	1	3299	5401	64	466104	16.1841667
2010/11/15	5400	GC-MHLANGF-BF_ASS-Joh	1292	5357	6692	104	812115	28.1984375
2010/11/16	5400	GC-MHLONGMT-BF_ASS-R	2069	72	7469	129	954416	33.1394444
2010/11/17	5400	GC-VSTAVEL-BF_ASS-Mere	1	28	5401	83	515661	17.9048958
2010/11/18	5400	GC-MHLANGF-BF_ASS-Joh	1383	12250	6783	132	991574	34.4296528
2010/11/19	5400	GC-VSTAVEL-BF_ASS-Mere	2912	80	8312	75	559551	19.4288542
2010/11/20	3600	GC-MHLANGF-BF_ASS-Joh	2	58	3602	3	17564	0.60986111
2010/11/21	3600	GC-VSTAVEL-BF_ASS-Mere	1	64	3601	1	3601	0.12503472
2010/11/22	3600	GC-VSTAVEL-BF_ASS-Mere	2512	3585	6112	114	850409	29.5280903
2010/11/23	5400	GC-MHLANGF-BF_ASS-Joh	702	16921	6102	115	915170	31.7767361
2010/11/24	2700	GC-MHLONGMT-BF_ASS-L	1336	268	4036	82	637753	22.1442014
2010/11/25	5400	GC-VSTAVEL-BF_ASS-Mere	4523	3242	9923	65	478536	16.6158333
2010/11/26	7200	GC-VSTAVEL-BF_ASS-Mere	5132	1104	12332	66	499311	17.3371875
2010/11/27	5400	GC-VSTAVEL-BF_ASS-Mere	5848	216	11248	4	55892	1.94069444
2010/11/29	9000	To be deleted	18751	23070	27751	101	727751	25.2691319
2010/11/30	5400	GC-MHLONGMT-BF_ASS-R	4740	226	10140	64	459314	15.9484028
2010/12/01	5400	GC-STEYNWJ-BF_ASS-Krug	1	115	5401	102	825632	28.6677778
2010/12/02	5400	GC-VSTAVEL-BF_ASS-Mere	6125	30	11525	58	480537	16.6853125
2010/12/03	1800	To be deleted	3	4939	1803	66	585446	20.3279861
2010/12/04	5400	GC-MHLONGMT-BF_ASS-L	2681	153	8081	4	33738	1.17145833
2010/12/05	5400	GC-STEYNWJ-BF_ASS-Krug	1	2769	5401	1	5401	0.18753472
2010/12/06	16200	GC-MHLANGF-BF_ASS-Joh	17070	5620	33270	83	580163	20.1445486
2010/12/07	3600	GC-MHLONGMT-BF_ASS-L	3839	1349	7439	84	624885	21.6973958
2010/12/08	5400	GC-VSTAVEL-BF_ASS Auck	6738	82	12138	89	667842	23.1889583
2010/12/09	5400	GC-VSTAVEL-BF_ASS Auck	1	9051	5401	105	882928	30.6572222
2010/12/10	5400	GC-MHLANGF-BF_ASS-Joh	320	446	5720	79	635100	22.0520833
2010/12/11	5400	GC-MHLONGMT-BF_ASS-L	5392	299	10792	6	52050	1.80729167
2010/12/12	5400	GC-VSTAVEL-BF_ASS Auck	5185	202	10585	3	26311	0.91357639
2010/12/13	5400	GC-VSTAVEL-BF_ASS-Mere	0	27	5400	199	1552589	53.9093403
2010/12/14	5400	GC-MHLONGMT-BF_ASS-L	2810	61	8210	88	664901	23.0868403
2010/12/15	5400	GC-VSTAVEL-BF_ASS Auck	2	26	5402	84	693290	24.0725694
2010/12/16	1800	To be deleted	1	62	1801	4	21438	0.744375
2010/12/17	3600	GC-VSTAVEL-BF_ASS-Mere	6528	81	10128	103	749400	26.0208333
2010/12/18	5400	GC-MHLANGF-BF_ASS-Joh	86	8460	5486	12	66981	2.32572917
2010/12/19	3600	GC-STEYNWJ-BF_ASS-Krug	1718	1191	5318	1	5318	0.18465278
2010/12/20	5400	GC-MHLANGF-BF_ASS-Joh	19	55	5419	87	712945	24.7550347
2010/12/21	5400	GC-VSTAVEL-BF_ASS-Mere	11865	45	17265	45	347232	12.0566667
2010/12/22	5400	GC-MHLONGMT-BF_ASS-L	6737	49	12137	79	625647	21.7238542
2010/12/23	5400	GC-VSTAVEL-BF_ASS-Mere	4	66	5404	37	288519	10.0180208
2010/12/24	5400	GC-MHLONGMT-BF_ASS-L	5149	44	10549	23	163533	5.67822917
2010/12/25	3600	GC-STEYNWJ-BF_ASS-Krug	3020	29479	6620	2	15234	0.52895833
2010/12/27	5400	GC-STEYNWJ-BF_ASS-Krug	1970	11698	7370	6	36905	1.28142361
2010/12/28	3600	GC-VSTAVEL-BF_ASS-Mere	3	8333	3603	43	315511	10.9552431
2010/12/29	3600	GC-STEYNWJ-BF_ASS-Krug	7148	129	10748	82	638619	22.1742708
2010/12/30	5400	GC-MHLONGMT-BF_ASS-L	5066	5329	10466	67	407237	14.1401736
2010/12/31	7200	GC-VSTAVEL-BF_ASS Auck	12212	47	19412	20	151892	5.27402778
2011/01/01	3600	GC-VSTAVEL-BF_ASS Auck	9352	144	12952	1	12952	0.44972222
2011/01/02	5400	GC-MHLANGF-BF_ASS-Joh	6809	63	12209	2	18183	0.63135417
2011/01/03	10800	GC-MHLANGF-BF_ASS-Joh	3000	11153	13800	139	1066767	37.0405208
2011/01/04	5400	GC-VSTAVEL-BF_ASS Auck	6019	375	11419	119	898297	31.1908681
2011/01/05	3600	GC-STEYNWJ-BF_ASS-Krug	1	215	3601	121	945931	32.8448264
2011/01/06	3600	To be deleted	3	82	3603	139	966934	33.5740972

Data - Region 1 - Fulfilment

CREATED_DATE	ESTIMATED_DURATION (Seconds)	AREA_NAME_DESC	TOTAL_TIME_EN_ROUTE (Seconds)	TOTAL_TIME_ON_SITE (Seconds)	Total Time (Seconds)	Number of jobs	Time tech's required per day (Seconds)	Number of Tech's required
2010/11/02	90000	GC-MHLANGF-	9661	109181	99661	1	99661	3.46045139
2010/11/03	6960	GC-MHLANGF-	18	347	6978	3	457929	15.9003125
2010/11/04	41400	GC-STEYNWJ-B	8095	44549	49495	6	333301	11.5729514
2010/11/05	14220	GC-MHLANGF-	2	23	14222	14	538035	18.6817708
2010/11/08	25200	GC-MHLANGF-	2119	26731	27319	25	676090	23.4753472
2010/11/09	72000	GC-MHLANGF-	19	60828	72019	17	752215	26.1185764
2010/11/10	2700	To be deleted	1	1422	2701	17	761313	26.4344792
2010/11/11	10800	GC-VSTAVEL-B	1	12917	10801	16	586787	20.3745486
2010/11/12	162000	GC-MHLANGF-	8136	101886	170136	21	777896	27.0102778
2010/11/15	5400	GC-VSTAVEL-B	0	0	5400	23	795161	27.6097569
2010/11/16	10800	GC-MHLANGF-	108	7948	10908	21	387021	13.4382292
2010/11/17	5400	GC-MHLANGF-	7	77	5407	21	472921	16.4208681
2010/11/18	3600	GC-MHLANGF-	10	425	3610	18	736175	25.5616319
2010/11/19	2700	To be deleted	0	30	2700	15	237038	8.23048611
2010/11/22	10800	GC-STEYNWJ-B	3021	10556	13821	26	810088	28.1280556
2010/11/23	3600	To be deleted	58	2612	3658	14	439450	15.2586806
2010/11/24	171300	GC-VSTAVEL-B	6	35934	171306	9	450109	15.6287847
2010/11/25	3600	To be deleted	2	1211	3602	18	599368	20.8113889
2010/11/26	3600	To be deleted	2	24	3602	8	133270	4.62743056
2010/11/29	3600	To be deleted	3	13889	3603	15	468173	16.2560069
2010/11/30	72000	GC-MHLONGM	16608	53916	88608	20	536718	18.6360417
2010/12/01	3600	To be deleted	2	2769	3602	17	391796	13.6040278
2010/12/02	7200	GC-STEYNWJ-B	2342	5531	9542	17	433192	15.0413889
2010/12/03	3600	GC-MHLANGF-	159	5179	3759	10	549957	19.0957292
2010/12/06	3600	To be deleted	2	5910	3602	16	490528	17.0322222
2010/12/07	10800	GC-MHLANGF-	3322	13483	14122	14	470742	16.3452083
2010/12/08	7200	GC-STEYNWJ-B	1629	179	8829	16	625384	21.7147222
2010/12/09	10800	GC-VSTAVEL-B	1566	355	12366	13	630014	21.8754861
2010/12/10	10800	GC-MHLANGF-	1	86	10801	16	591786	20.548125
2010/12/13	7200	GC-STEYNWJ-B	1	177	7201	16	422700	14.6770833
2010/12/14	3600	GC-MHLANGF-	13	782	3613	19	313420	10.8826389
2010/12/15	4800	GC-MHLONGM	5	14391	4805	14	340109	11.8093403
2010/12/17	3600	To be deleted	2	30	3602	6	171877	5.96795139
2010/12/20	10800	GC-VSTAVEL-B	3	242	10803	12	374557	13.0054514
2010/12/21	12600	GC-MHLONGM	4287	14602	16887	15	229537	7.97003472
2010/12/22	3600	To be deleted	4	14045	3604	7	97978	3.40201389
2010/12/23	3600	GC-MHLANGF-	2	26229	3602	14	272683	9.46815972
2010/12/24	7200	GC-STEYNWJ-B	4933	4412	12133	4	75773	2.63100694
2010/12/28	10800	GC-MHLANGF-	1	550	10801	6	159517	5.53878472
2010/12/29	14400	GC-MHLONGM	3501	23563	17901	7	384260	13.3423611
2010/12/30	10800	GC-STEYNWJ-B	10	90	10810	4	73517	2.55267361
2011/01/03	7200	GC-MHLANGF-	10600	9482	17800	4	56934	1.976875
2011/01/04	39600	GC-STEYNWJ-B	2	18731	39602	16	1151723	39.9903819
2011/01/05	82800	GC-VSTAVEL-B	30091	111979	112891	15	428369	14.8739236
2011/01/06	36000	GC-MHLONGM	6633	88804	42633	13	411774	14.2977083
2011/01/07	14400	GC-MHLONGM	5	16708	14405	9	159114	5.52479167
2011/01/10	3600	To be deleted	2	7587	3602	18	370161	12.8528125
2011/01/11	3600	To be deleted	2	58	3602	19	310735	10.7894097
2011/01/12	7200	GC-MHLONGM	2	147	7202	13	450882	15.655625
2011/01/13	7200	GC-STEYNWJ-B	33	9207	7233	13	375313	13.0317014
2011/01/14	14400	GC-MHLONGM	0	0	14400	16	346622	12.0354861
2011/01/17	10800	GC-MHLONGM	0	0	10800	14	495590	17.2079861
2011/01/18	3600	GC-MHLANGF-	1	914	3601	16	332242	11.5361806
2011/01/19	54000	GC-MHLANGF-	2	36724	54002	12	371415	12.8963542
2011/01/20	10800	GC-MHLANGF-	1	36	10801	12	239672	8.32194444
2011/01/21	7200	GC-MHLONGM	2	9428	7202	10	190590	6.61770833
2011/01/24	6960	GC-MHLANGF-	5	8957	6965	10	282653	9.81434028
2011/01/25	48300	GC-MHLANGF-	58	46169	48358	12	518989	18.0204514
2011/01/26	18000	GC-STEYNWJ-B	3705	8650	21705	14	335032	11.6330556
2011/01/27	7200	GC-MHLANGF-	12	7075	7212	13	240484	8.35013889

Appendix B -Example of Additive Model Results

Additive XLMiner® results for region 1 - Assurance

XLMiner : Time Series - Holt Winter Forecasting Method(Additive Model)

Output Navigator		
Inputs	Fitted Model	Forecast
Elapsed Time	Error Measures(Training)	Error Measures(Validation)

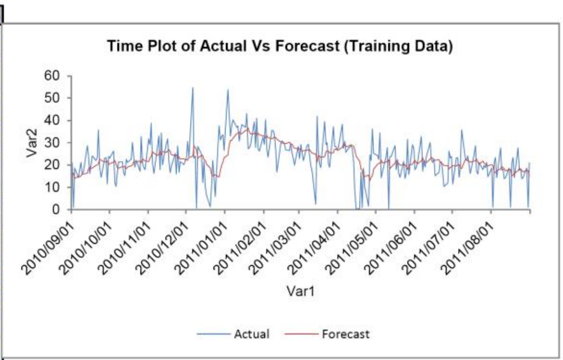
Inputs

Data	
# Records in input data	261
Input data	01 ASS!$D$1:$E$261
Selected variable	Var2

Parameters/Options	
Alpha (Level)	0.15
Beta (Trend)	0.005
Gamma (Seasonality)	0.005
Season length	5
Number of seasons	52
Forecast	Yes
#Forecasts	100

Fitted Model

Var1	Actual	Forecast	Residuals
2010/09/01	21.0952083	15.6892953	5.40591302
2010/09/02	1.05756944	16.3882153	-15.3306458
2010/09/03	18.7105901	14.0091265	4.70146361
2010/09/06	14.3051736	14.9317305	-0.62655692
2010/09/07	17.9948611	14.7741428	3.22071831
2010/09/08	21.204375	15.276699	5.92767598
2010/09/09	15.9963194	15.9641725	0.0321469
2010/09/10	17.0776736	15.9845807	1.09309289
2010/09/13	28.70625	16.3505204	12.3557296
2010/09/14	24.5148958	18.1735986	6.34129727
2010/09/15	16.1886804	19.1750587	-2.98637826
2010/09/16	19.8526042	18.512995	1.33960921
2010/09/17	24.1528472	18.747639	5.4052082
2010/09/20	22.0456944	19.8251038	2.22059068
2010/09/21	23.286458	20.11159	3.17486798
2010/09/22	35.8302084	20.6053085	15.2248999
2010/09/23	18.5828125	22.7138459	-4.13103337
2010/09/24	14.4276042	22.1615932	-7.73398908
2010/09/27	23.1922917	21.2612103	1.93108139
2010/09/28	23.2415625	21.5146752	1.72688731
2010/09/29	11.4519792	21.8476726	-10.3956934
2010/09/30	23.9201389	20.0169062	3.9032327
2010/10/01	23.1098264	20.6465545	2.46327184
2010/10/04	26.2154514	21.3165589	4.89889253
2010/10/05	12.0180903	22.0162751	-9.99818478
2010/10/06	10.3504514	20.5321443	-10.1816929
2010/10/07	17.0649653	18.7875626	-1.72259729
2010/10/08	21.3644097	18.5563114	2.80809836
2010/10/11	21.4693056	19.2777444	2.19156113
2010/10/12	16.6543051	19.4953712	-2.84106611
2010/10/13	15.2193749	19.0767191	-3.85734423
2010/10/14	22.7247917	18.3141748	4.41061687
2010/10/15	21.2275694	19.0241951	2.20337437
2010/10/18	22.6161458	19.6538796	2.96226622
2010/10/19	30.1135065	19.9678819	10.1456246
2010/10/20	23.709028	21.5048126	2.20421539
2010/10/21	19.1232292	21.7030856	-2.57985648
2010/10/22	22.1426389	21.3663559	0.77628303
2010/10/25	17.2253125	21.7953334	-4.57002088
2010/10/26	32.8415972	21.0145041	11.8270932
2010/10/27	20.7518746	22.7756474	-2.0237728
2010/10/28	19.1232292	22.3219622	-3.19873299
2010/10/29	17.9557639	21.9087726	-3.95300873
2010/11/01	31.7103819	21.6041958	10.1061862
2010/11/02	29.0952431	23.1040535	5.99118951
2010/11/03	38.7743056	23.9361365	14.838169
2010/11/04	20.8533333	26.0245869	-5.17125353
2010/11/05	16.1841667	25.328672	-9.14450536
2010/11/08	28.1984375	24.3175871	3.88085041
2010/11/09	33.1394444	24.8739516	8.26549282
2010/11/10	17.9048958	26.0942813	-8.18938548
2010/11/11	34.4296528	24.6357893	9.79386345
2010/11/12	20.0387152	26.1712105	-6.1324953
2010/11/15	29.6531253	25.6729985	3.98012674
2010/11/16	31.7767361	26.2686775	5.50805866
2010/11/17	22.1442014	27.0091789	-4.86497753



Error Measures (Training)

MAPE	145.227168
MAD	5.93531787
MSE	65.6882257

Forecast

Var1	Forecast	LCI	UCI
2011/09/01	12.2359199	-3.64954161	28.1213814
2011/09/02	11.8288035	-4.05665801	27.714265
2011/09/03	13.1963755	-2.689086	29.081837
2011/09/04	12.5861331	-3.29932844	28.4715946
2011/09/05	12.3857683	-3.49969323	28.2712298
2011/09/06	11.8249446	-4.0605169	27.7104061
2011/09/07	11.4178282	-4.4676333	27.3032897
2011/09/08	12.7854002	-3.10006128	28.6708618
2011/09/09	12.1751578	-3.71030372	28.0606193
2011/09/10	11.974793	-3.91066852	27.8602545
2011/09/11	11.4139693	-4.47149218	27.2994309
2011/09/12	11.0068529	-4.87860858	26.8923145
2011/09/13	12.374425	-3.51103657	28.2598865
2011/09/14	11.7641825	-4.12127901	27.649644
2011/09/15	11.5638177	-4.3216438	27.4492792
2011/09/16	11.0029941	-4.88246746	26.8884556
2011/09/17	10.5958777	-5.28958386	26.4813392
2011/09/18	11.9634497	-3.92201185	27.8489112
2011/09/19	11.3532072	-4.53225429	27.2386687
2011/09/20	11.1528424	-4.73261908	27.038304
2011/09/21	10.5920188	-5.29344275	26.4774803
2011/09/22	10.1849024	-5.70055915	26.0703639
2011/09/23	11.5524744	-4.33298713	27.4379359
2011/09/24	10.9422319	-4.94322957	26.8276935
2011/09/25	10.7418672	-5.14359437	26.6273287
2011/09/26	10.1810435	-5.70441803	26.066505
2011/09/27	9.77392709	-6.11153443	25.6593886
2011/09/28	11.1414991	-4.74396242	27.0269606
2011/09/29	10.5312567	-5.35420486	26.4167182
2011/09/30	10.3308919	-5.55456965	26.2163534
2011/10/01	9.7700682	-6.11539332	25.6555297
2011/10/02	9.36295181	-6.52250971	25.2484133
2011/10/03	10.7305238	-5.1549377	26.6159853
2011/10/04	10.1202814	-5.76518014	26.0057429
2011/10/05	9.91991658	-5.96554493	25.8053781
2011/10/06	9.35909292	-6.5263686	25.2445544
2011/10/07	8.95197652	-6.933485	24.837438
2011/10/08	10.3195485	-5.56591298	26.2050101

Appendix C -Example of Multiplicative Model Results

Multiplicative XLMiner® results for region 1 - Assurance

XLMiner : Time Series - Holt Winter Forecasting Method(Multiplicative Model)

Output Navigator		
Inputs	Fitted Model	Forecast
Elapsed Time	Error Measures(Training)	Error Measures(Validation)

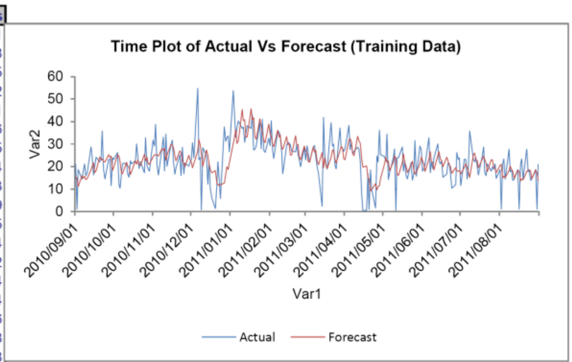
Inputs

Data	
# Records in input data	261
Input data	01 ASS!$D$1:$E$261
Selected variable	Var2

Parameters/Options	
Alpha (Level)	0.2
Beta (Trend)	0.05
Gamma (Seasonality)	0.05
Season length	5
Number of seasons	52
Forecast	Yes
#Forecasts	100

Fitted Model

Var1	Actual	Forecast	Residuals
2010/09/01	21.0952083	15.348875	5.74633331
2010/09/02	1.05756944	14.8052083	-13.7476388
2010/09/03	18.7105901	11.1155575	7.59503265
2010/09/06	14.3051736	15.9123899	-1.60721632
2010/09/07	17.9948611	14.802538	3.19232311
2010/09/08	21.204375	15.7215682	5.48280676
2010/09/09	15.9963194	14.2130259	1.78329355
2010/09/10	17.0776736	14.5929094	2.48476424
2010/09/13	28.70625	18.609817	10.096433
2010/09/14	24.5148958	20.072256	4.44263979
2010/09/15	16.1886804	21.6922829	-5.5036025
2010/09/16	19.8526042	17.3692723	2.48333184
2010/09/17	24.1528472	18.0339434	6.11890382
2010/09/20	22.0456944	24.224738	-2.17904354
2010/09/21	23.286458	22.9387756	0.3476824
2010/09/22	35.8302084	23.3662924	12.463916
2010/09/23	18.5828125	22.3025484	-3.71973588
2010/09/24	14.4276042	21.9929032	-7.56529908
2010/09/27	23.1922917	25.3035311	-2.11123947
2010/09/28	23.2415625	24.0563962	-0.81483369
2010/09/29	11.4519792	24.670157	-13.2181778
2010/09/30	23.9201389	18.3210235	5.59911538
2010/10/01	23.1098264	19.5519122	3.55791415
2010/10/04	26.2154514	25.2728969	0.94255454
2010/10/05	12.0180903	24.6405585	-12.6224682
2010/10/06	10.3504514	22.1975554	-11.8471039
2010/10/07	17.0649653	16.9914979	0.0734674
2010/10/08	21.3644097	16.8846436	4.47976609
2010/10/11	21.4693056	21.89426	-0.42495441
2010/10/12	16.6543051	20.4363482	-3.78204313
2010/10/13	15.2193749	19.6352867	-4.41591183
2010/10/14	22.7247917	16.4359124	6.28887932
2010/10/15	21.2275694	17.7741417	3.4534277
2010/10/18	22.6161458	22.5177688	0.09837699
2010/10/19	30.1135065	21.00098	9.11252648
2010/10/20	23.709028	22.8892033	0.81982468
2010/10/21	19.1232292	20.8853512	-1.76212206
2010/10/22	22.1426389	20.5922045	1.55043436
2010/10/25	17.2253125	25.4017538	-8.17644131
2010/10/26	32.8415972	22.5136006	10.3279967
2010/10/27	20.7518746	24.3189676	-3.56709302
2010/10/28	19.1232292	21.2676969	-2.1444677
2010/10/29	17.9557639	21.015779	-3.06001509
2010/11/01	31.7103819	24.3146065	7.39577546
2010/11/02	29.0952431	25.26183	3.83341301
2010/11/03	38.7743056	25.1788995	13.5954061
2010/11/04	20.8533333	25.3225273	-4.46919399
2010/11/05	16.1841667	24.710547	-8.52638038
2010/11/08	28.1984375	27.9873679	0.21106962
2010/11/09	33.1394444	27.3184724	5.82097202
2010/11/10	17.9048958	27.9568589	-10.0519631
2010/11/11	34.4296528	22.7927749	11.6368779
2010/11/12	20.0387152	25.2038698	-5.16515464
2010/11/15	29.6531253	29.87664	-0.22351473
2010/11/16	31.7767361	29.3194013	2.45733485
2010/11/17	22.1442014	28.5587617	-6.41456035



Error Measures (Training)

MAPE	135.315306
MAD	5.83889715
MSE	64.1297779

Forecast

Var1	Forecast	LCI	UCI
2011/09/01	10.5455293	-5.15036043	26.2414191
2011/09/02	8.47428243	-7.22160731	24.1701722
2011/09/03	10.0989209	-5.59696886	25.7948106
2011/09/04	8.1267779	-7.56911185	23.8226676
2011/09/05	7.96745929	-7.72843045	23.663349
2011/09/06	6.97925528	-8.71663447	22.675145
2011/09/07	5.40056705	-10.2953227	21.0964568
2011/09/08	6.14942625	-9.5464635	21.845316
2011/09/09	4.67886835	-11.0170214	20.3747581
2011/09/10	4.27371786	-11.4221719	19.9696076
2011/09/11	3.41298124	-12.2829085	19.108871
2011/09/12	2.32685166	-13.3690381	18.0227414
2011/09/13	2.19993161	-13.4959581	17.8958214
2011/09/14	1.2309588	-14.4649309	16.9268485
2011/09/15	0.57997642	-15.1159133	16.2758662
2011/09/16	-0.1532928	-15.8491825	15.5425969
2011/09/17	-0.74686373	-16.4427535	14.949026
2011/09/18	-1.74956302	-17.4454528	13.9463267
2011/09/19	-2.21695075	-17.9128405	13.478939
2011/09/20	-3.11376501	-18.8096548	12.5821247
2011/09/21	-3.71956684	-19.4154566	11.9763229
2011/09/22	-3.82057912	-19.5164689	11.8753106
2011/09/23	-5.69905765	-21.3949474	9.99683209
2011/09/24	-5.6648603	-21.36075	10.0310294
2011/09/25	-6.80750645	-22.5033962	8.8883833
2011/09/26	-7.28584088	-22.9817306	8.41004886
2011/09/27	-6.8942945	-22.5901842	8.80159524
2011/09/28	-9.64855229	-25.344442	6.04733746
2011/09/29	-9.11276985	-24.8086596	6.5831199
2011/09/30	-10.5012479	-26.1971376	5.19464186
2011/10/01	-10.8521149	-26.5480047	4.84377482
2011/10/02	-9.96800989	-25.6638996	5.72787985
2011/10/03	-13.5980469	-29.2939367	2.09784282
2011/10/04	-12.5606794	-28.2565691	3.13521035
2011/10/05	-14.1949893	-29.8908791	1.50090043
2011/10/06	-14.418389	-30.1142787	1.27750078
2011/10/07	-13.0417253	-28.737615	2.65416446
2011/10/08	-17.5475416	-33.2434313	-1.85165181

Appendix D -Example of Ad Hoc Models Spread sheets

Ad Hoc model (with monthly and weekly factors) for region 1 - Assurance

Data

	September	September	September	September	September	September	September	September	September	September	September	September	September	September
				Week 36					Week 37					Week 38
	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday
	2010/09/01	2010/09/02	2010/09/03	2010/09/06	2010/09/07	2010/09/08	2010/09/09	2010/09/10	2010/09/13	2010/09/14	2010/09/15	2010/09/16	2010/09/17	2010/09/20
	21.09520833	1.057569444	18.71059011	14.30517361	17.99486111	21.204375	15.9963194	17.07767361	28.70625	24.51489583	16.18868039	19.85260417	24.1528472	22.0456944

September	September	September	September	September	September	September	September	October	October	October	October	October	October
				Week 39					Week 40				
Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday
2010/09/21	2010/09/22	2010/09/23	2010/09/24	2010/09/27	2010/09/28	2010/09/29	2010/09/30	2010/10/01	2010/10/04	2010/10/05	2010/10/06	2010/10/07	2010/10/08
23.286458	35.83020839	18.5828125	14.42760417	23.19229167	23.2415625	11.4519792	23.92013889	23.10982639	26.21545139	12.01809028	10.35045144	17.0649653	21.3644097

	Sum	Count	Average	Factors
Monday	1345.8411	52	25.8816	1.131106729
Tuesday	1217.6865	51	23.8762	1.043466386
Wednesday	1237.1195	53	23.3419	1.020114513
Thursday	1109.7326	52	21.3410	0.932670313
Friday	1033.8115	52	19.8810	0.868862749

	Sum	Count	Average	Factors
January	744.9706257	21	35.4748	1.550361607
February	569.132712	20	28.4566	1.243645789
March	588.6472908	23	25.5934	1.118511528
April	420.5144104	21	20.0245	0.875134367
May	468.4537839	22	21.2934	0.930587515
June	456.9410058	22	20.7700	0.907717281
July	432.3267352	21	20.5870	0.899717048
August	381.6949648	23	16.5954	0.725273394
September	436.8358	22	19.8562	0.867778111
October	433.0209	21	20.6200	0.901161608
November	539.7084	22	24.5322	1.072135364
December	499.8574	23	21.7329	0.94979834

Total Sum	Total Count	Base Value
5972.1039	261	22.8816

Week	Average	Factors		Average	Factors		Average	Factors
1	41.67269449	1.821229738	19	20.00143038	0.87412634	37	22.68305552	0.991321914
2	35.61201397	1.556358658	20	19.97795147	0.87310023	38	22.8345555	0.997942947
3	32.83369437	1.434937225	21	19.90731239	0.87001308	39	20.98315972	0.917031043
4	32.35659731	1.414086561	22	22.87740267	0.9998155	40	17.40267362	0.760552374
5	30.61859022	1.338130105	23	23.00836116	1.00553881	41	19.45906933	0.850423429
6	29.65164582	1.295871549	24	22.38027767	0.97808956	42	23.54090968	1.028812879
7	29.45439668	1.287251132	25	17.38068742	0.75959151	43	21.57955547	0.943095440
8	24.95639579	1.090674139	26	19.34309722	0.84535508	44	27.32348611	1.194123540
9	25.69235408	1.122837865	27	23.05489584	1.00757252	45	26.74222914	1.168720756
10	23.92774291	1.045718725	28	21.10525684	0.92236708	46	23.89355552	1.044224627
11	21.96313896	0.959859263	29	21.49990278	0.93961436	47	21.61401382	0.944601380
12	27.66299994	1.208961378	30	18.51489574	0.80916003	48	23.90950007	1.044921455
13	29.72497228	1.299076149	31	15.72863886	0.68739171	49	26.21465267	1.145663980
14	29.79005563	1.301920500	32	18.35452083	0.80215113	50	14.98908331	0.655070775
15	17.35532642	0.758483150	33	15.72863886	0.68739171	51	10.85497218	0.474396925
16	9.439437478	0.412533542	34	18.35452083	0.80215113	52	32.3716527	1.414744530
17	21.94095144	0.958889598	35	12.12630549	0.52995825			
18	22.49283341	0.983008601	36	17.31568056	0.7567505			

Forecast 2011 Monthly Factors

January	January	January	January	January	January	January	January	January	January	January	January	January	January
Week 1					Week 2					Week 3			
Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday
2011/01/03	2011/01/04	2011/01/05	2011/01/06	2011/01/07	2011/01/10	2011/01/11	2011/01/12	2011/01/13	2011/01/14	2011/01/17	2011/01/18	2011/01/19	2011/01/20
40	37	36	33	31	40	37	36	33	31	40	37	36	33

January	January	January	January	January	January	January	February	February	February	February	February	February	February
	Week 4					Week 5					Week 6		
Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday
2011/01/21	2011/01/24	2011/01/25	2011/01/26	2011/01/27	2011/01/28	2011/01/31	2011/02/01	2011/02/02	2011/02/03	2011/02/04	2011/02/07	2011/02/08	2011/02/09
31	40	37	36	33	31	40	30	29	27	25	32	30	29

Forecast 2011 Weekly Factors

January	January	January	January	January	January	January	January	January	January	January	January	January	January
Week 1					Week 2					Week 3			
Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday
2011/01/03	2011/01/04	2011/01/05	2011/01/06	2011/01/07	2011/01/10	2011/01/11	2011/01/12	2011/01/13	2011/01/14	2011/01/17	2011/01/18	2011/01/19	2011/01/20
47	43	43	39	36	40	37	36	33	31	37	34	33	31

January	January	January	January	January	January	January	February	February	February	February	February	February	February
	Week 4					Week 5					Week 6		
Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday	Thursday	Friday	Monday	Tuesday	Wednesday
2011/01/21	2011/01/24	2011/01/25	2011/01/26	2011/01/27	2011/01/28	2011/01/31	2011/02/01	2011/02/02	2011/02/03	2011/02/04	2011/02/07	2011/02/08	2011/02/09
29	37	34	33	30	28	35	32	31	29	27	34	31	30

	2011/01/03	2011/01/04	2011/01/05	2011/01/06	2011/01/07	2011/01/10	2011/01/11	2011/01/12	2011/01/13	2011/01/14	2011/01/17	2011/01/18	2011/01/19	2011/01/20
Data	53.89395872	44.06354167	33.00427083	37.07413194	40.3275693	36.9341319	37.60621528	30.76961806	34.55232639	38.19777817	36.93048611	43.1857292	27.3286458	27.63923611
Forecast M	40.1258	37.0168	36.1883	33.0863	30.8227	40.1258	37.0168	36.1883	33.0863	30.8227	40.1258	37.0168	36.1883	33.0863
Forecast W	47.1363	43.4841	42.5109	38.8669	36.2079	40.2810	37.1599	36.3283	33.2143	30.9420	37.1384	34.2609	33.4941	30.6230

	2011/01/21	2011/01/24	2011/01/25	2011/01/26	2011/01/27	2011/01/28	2011/01/31	2011/02/01	2011/02/02	2011/02/03	2011/02/04	2011/02/07	2011/02/08
Data	29.08437461	39.27486106	27.91274306	40.99013889	27.2881597	26.3170838	32.595625	29.30777778	40.41270833	27.17822917	23.59861083	35.5718749	35.4082292
Forecast M	30.8227	40.1258	37.0168	36.1883	33.0863	30.8227	40.1258	29.6935	29.0290	26.5407	24.7249	32.1875	29.6935
Forecast W	28.5280	36.5988	33.7630	33.0074	30.1780	28.1134	34.6329	31.9495	31.2345	28.5571	26.6034	33.5392	30.9405

	2011/01/03	2011/01/04	2011/01/05	2011/01/06	2011/01/07	2011/01/10	2011/01/11	2011/01/12	2011/01/13	2011/01/14	2011/01/17	2011/01/18	2011/01/19	2011/01/20
Abs(m-x) M	17.2441514	14.13512846	13.30672566	10.20466085	7.94110083	17.2441514	14.13512846	13.30672566	10.20466085	7.941100828	17.2441514	14.1351285	13.3067257	10.20466085
Abs(m-x) W	24.25464095	20.60243168	19.62929625	15.98526079	13.3262277	17.3993644	14.27831528	13.44670808	10.33264399	8.060328146	14.25678843	11.3792322	10.6125039	7.741387778

	2011/01/21	2011/01/24	2011/01/25	2011/01/26	2011/01/27	2011/01/28	2011/01/31	2011/02/01	2011/02/02	2011/02/03	2011/02/04	2011/02/07	2011/02/08
Abs(m-x) M	7.941100828	17.2441514	14.13512846	13.30672566	10.2046609	7.94110083	17.2441514	6.811918479	6.147402762	3.659035008	1.843286425	9.30586781	6.81191848
Abs(m-x) W	5.64634974	13.71714074	10.88139743	10.12581031	7.29641352	5.23181788	11.75126923	9.067845455	8.352844049	5.675425902	3.721728263	10.6575519	8.05887148

	SUM	COUNT	MAD
Abs(m-x) M	1030.4089	261	3.947926753
Abs(m-x) W	1330.0740	261	5.096069009