Lasse Huusko

DEVELOPING A FORECASTING MODEL FOR DOCTOR´S APPOINTMENTS IN HEALTHCARE BUSINESS

Helsinki Metropolia University of Applied Sciences
Master's Degree in Industrial Management
Master's Thesis
6 May 2011
Instructors: Marjatta Huhta DSc (Tech) James Collins PhD Tiina Pohjonen PhD

PREFACE

This study was conducted during the spring 2011. This Master´s Thesis has introduced me a new field of science; forecasting in healthcare business. During this study I have learned a great deal about the forecasting processes. From a professional point of view, it is really good to have challenges outside your own field and I feel that it helps me to grow as a professional when I step outside my comfort zone.

I would like to thank all my teachers and superiors who have contributed to this Thesis. My special thanks are given to Tiina Pohjonen CEO of the Helsinki City Occupational HealthCare Centre, for providing an opportunity to investigate demand forecasting in the occupational healthcare sector. Special thanks are also given to my instructors James Collins and Marjatta Huhta and as well as other Metropolia teachers for valuable comments and opinions.

Last but not least, I would like to thank my wife for her patience during my studies which have taken a lot of my time during the academic year, and especially in the Master’s Thesis writing time.

6 May 2011 Lasse Huusko

Metropolia

Abstract

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Underutilization and over demand of experts in services companies is both inefficient and costly; particularly in organizations that employ highly educated professionals, for example doctors and other healthcare workers. The need for accurate forecasting is therefore a crucial business priority. This Thesis develops a demand forecasting model for doctor´s appointment at the city of Helsinki Occupational HealthCare Centre. The model is examined by applying it to doctor services at one of several business units at the centre.

The study draws upon forecasting theory. Through benchmarking and current state analysis and historical analysis of the case company data the variables deemed to predict demand are identified. Three different forecasting models are then examined in order to test which is most appropriate to the context and best serves to forecast actual service demand.

Given different demand trends over the period of a year, for example the seasonality found in the historical data, SPSS Statistics 19 Expert modeler was found to be the most appropriate model. The appropriateness of this model is tested by examining predicted demand and actual demand over a three month period, and by interviewing health care professionals in the case organization.

The Thesis discusses the wider implications for practice. The limitations of the study are discussed; particularly with regard to the evaluation of further variables that might improve the model. Avenues for further study are presented

Keywords	Demand, forecasting, forecasting process, time series analyses

Tiivistelmä

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Tutkimus rakentaa mallin terveydenhuollon kysynnän analysointiin ja lääkäripalveluiden ennustamiseen Helsingin kaupungin työterveyshuollon valitussa työterveyshuolto yksikössä.
Tutkimuksen analyysit perustuvat palveluliiketoiminnan sekä terveydenhuollon kirjallisuuteen ennustemenetelmistä.
Kirjallisuus osio esittelee ennuste menetelmien teoriaa sekä luo pohjan ennustemenetelmien käyttöönottamiseksi terveydenhuollon organisaatiossa.
Terveydenhuolto organisaation tarvitsee kerätä paras mahdollinen tieto asiakas segmentistä ennen ennustemenetelmien käyttöönottoa. Työterveyshuolto organisaation pitää myös päättää mitä tietoja ennustemallissa halutaan käyttää ja mitata. Organisaation tulee tutkia tuotettujen palveluiden taustatietoja vähintään 2-4 vuoden ajalta. Taustatiedot antavat informaatiota trendi- ja kausivaihteluista ja tätä tietoa tarvitaan oikean ennustemallin rakentamiseksi.
Nykytila-analyysi asiakaskunnasta antaa tietoa kohteena olevan yrityksen ikäjakaumasta sekä muita merkitseviä tekijöitä, joita ennustetta tekevän organisaation tulee ottaa huomioon rakentaessaan ennustemallia työterveyshuollossa.
Tutkimus analysoi ja vertailee kolmea erilaista ennustemenetelmää ja luo pohjan parhaalle mahdolliselle ennustetyökalulle.
Tulos- ja analyysi kappaleissa esitetään, että SPSS expert modeler tulisi ottaa käyttöön luotaessa ennustemalleja Helsingin kaupungin työterveyskeskuksessa. Ennusteita verrataan alkuvuoden 2011 toteumiin jotka vahvistavat että malli soveltuu käytettäväksi työterveyshuollon kysynnän ennustamiseen.
Jatkotutkimuksiin suositellaan että ennustemalliin otetaan tutkittavaksi diagnoosi, sairauspoissaolo sekä ikäjakauma tietoja.
Tutkimuksessa tuotettu ennustemalli pyrkii luomaan mahdollisimman tuotannollistaloudellisen kuvan terveydenhuollon ennustemenetelmistä.

Avainsanat	Kysyntä, ennustaminen, Ennustamisen prosessi, aikasarja analyysit

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1 Introduction

Underutilization and over demand of experts in services companies is both inefficient and costly; particularly in organizations that employ highly educated professionals, for example doctors and other healthcare workers. The need for accurate forecasting is therefore a crucial business priority. This Master's Thesis builds a forecasting model for doctor´s appointments demand at the city of Helsinki Occupational HealthCare Centre. The model is examined by applying it to doctor services at one of several business units at the centre.

Occupational HealthCare Centre (OHCC) with its 138 professionals aims at supporting the employee ability to work and strives to secure effective functioning of working communities. OHCC is responsible for providing healthcare services to almost 40,000 people employed by the city of Helsinki. Altogether, the OHCC customers represent more than 800 various occupations, for which a diverse supply of healthcare services is needed

Being an occupational healthcare centre, OHCC is focused on illnesses weakening the ability to work. OHCC evaluates the employees' health and ability to work, and provides a wide range of medical treatments. The main stakeholders of occupational healthcare OHCC is the city of Helsinki, represented by its strategy managers, work process managers and competent employees. OHCC provide services for the working communities from the points of view of their future, change and development.

In modern versatile environment, OHCC is facing many new business needs; the current approach does not offer the necessary flexibility and agility required for the present day healthcare provision. One of the most challenging needs for OHCC today is the need for predicting the doctor´s appointments demand on weekly and monthly bases. In this Thesis, the doctor's appointments demand was defined as a request for short and long medical examination, telephone calls and working conditions examinations conducted by doctors. The scope of this Thesis is limited to the customers demand for appointments for these categories only. For the purposes of the Thesis, these categories of medical services are divided into smaller groups, and the demand for their services is studied in detail. Finally, a model is suggested which helps to forecast the customer demand in OHCC.

To investigate the research problem, the research question was formulated in the following way:

How to improve the existing customer demand analyses in OHCC?

The study draws upon forecasting theory. Through benchmarking and current state analysis and historical analysis of the case company data the variables deemed to predict demand are identified. This Thesis clarifies the demand forecasting process for the OHCC. Forecasting model is based on data collection and results and analysis of the forecasting tools. Alternative forecasting models have been tested in order to identify their functionality in the study´s case organization. The Figure 1 shows the overall framework of this Thesis. Forecasting theory and mathematical modeling are giving the foundation for the proposed model. The existing patient data and management interviews are giving the final implementation for the proposed model and also for the research question.

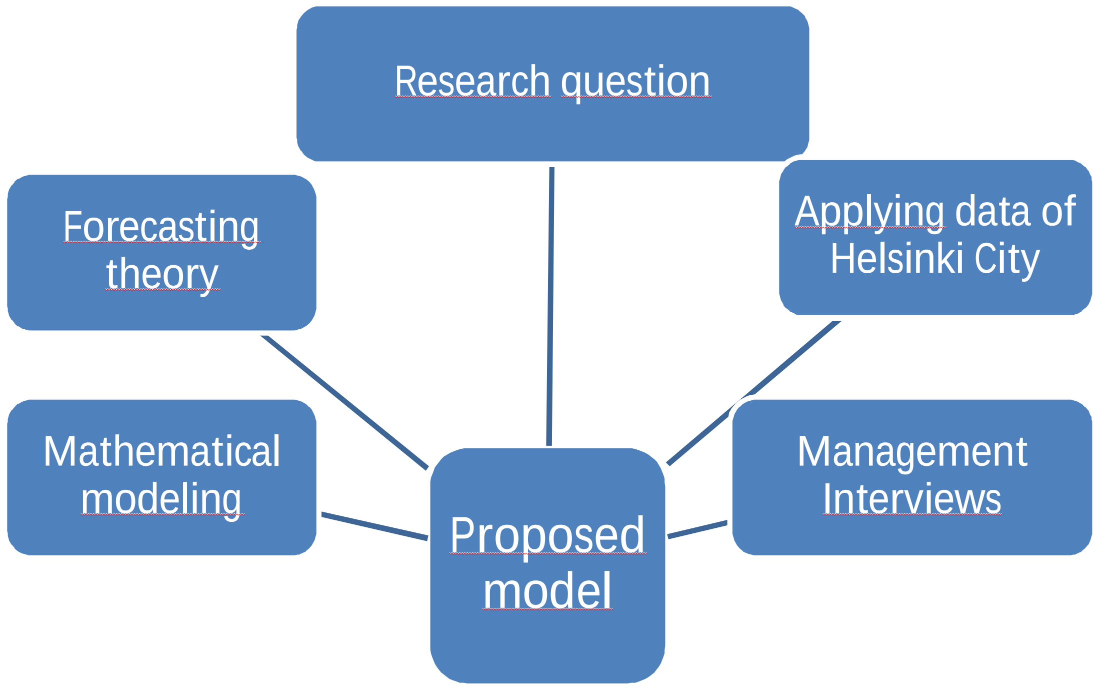


Figure 1. Research design.

The outcome of this Thesis represents a tool and model for predicting demand on a monthly level. This study is not only providing a model for sales forecasting. This Thesis is more complex than normal sales forecasting process, because of the complexity of the whole healthcare process, which is presented in the Figure 2 at the literature analysis section. Need, demand and supply of the healthcare services are tight in the healthcare service provision.

The present state is that, the study's case organization does not have a model for demand forecasting. The organization has set goals and targets for the nursing staff (doctors, nurses, physiotherapists and psychologies). These goals are only expressing the targets for each professional group, which they should achieve on a monthly period. Proposed forecasting model is based on statistical analyses. The historical background data is gathered from the patient databases, which include all the medical data from the beginning of the year 2004 on the present date. This Thesis background data is based on the three year period.

The first section of this Thesis provides knowledge for the existing forecasting models theories from the literature. Section Research Method and Material introduces the used research method and mathematical and statistical analyses, which are constructing the ground for the practical implementation. In section four, The Current status analyses of the study´s case organization, provides an overview and knowledge to build the forecasting model. On the section five three different forecasting models are then examined in order to test which is most appropriate to the context and best serves to forecast actual service demand. The last sections suggest the actual model for the case organization and its business unit.

Modern healthcare business has changed the traditional doctor-patient relationship. Nowadays patient is treated by a team of healthcare professionals, each specializing in one aspect of healthcare. This kind of shared healthcare depends critically on the ability to share information between care providers and caring team. From the patients' point of view, what once was a doctor-patient relationship is now becoming a customer-company relationship. The customers expect the company to know everything about their contracts, schedules, and medical histories from the first contact via telephone or online reservation system through the completion of a medical treatment.

Healthcare management systems must effectively address the needs of its three major players: the clinicians, administrators, and patients. From the clinicians' perspective, performance is measured by speed, reliability, and best clinical practices.

The main focus of this Thesis is to help the healthcare managers to identify and predict the changing business environment.

2 Forecasting Theory

This section introduces the forecasting theory, different forecasting methods and how organizations should try to develop the forecasting process and how to proceed and manage the forecasting errors. This section builds the ground for the whole Thesis.

The overall process overview of the healthcare business can be illustrated in Figure 2 (Figure 2 Provision, need and demand for healthcare services (Vissers 1998:79-80)). Figure 2 shows that demand for healthcare services is not the same as need for healthcare services. Therefore healthcare management is concentrated on the overlap between the need, demand and supply of services, as illustrated in Figure 2.

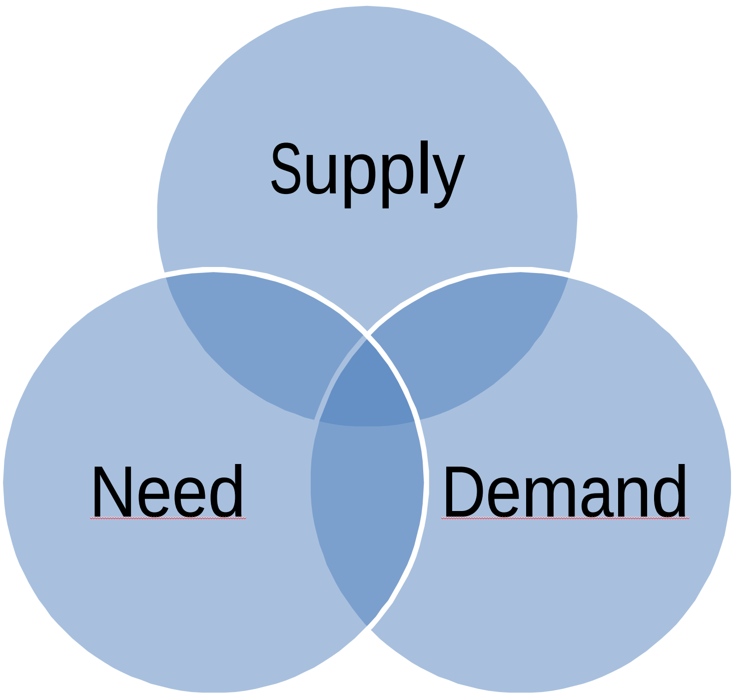


Figure 2. Supply, need and demand for healthcare services (Vissers 1998:79-80).

In Figure 2, demand illustrates possible patient's wants. Need stands for what the body of professional opinion approves as a lawful need. Supply represents the way resources are provided and organized in healthcare organization. In real world overlaps do not usually occur, as Figure 2 illustrates. The difference between need, demand and supply is necessary because of the demand structure in healthcare. Demand for the healthcare services is strongly influenced by the supply. Nursing staff and nursing specialists have influence on the demand for services, because of the decisions made by them on the length of stay in case of an admission, or on the number of revisits in case of an outpatient treatment, or on the amount of diagnostic services needed. Literature consider healthcare as a supply-driven system. When healthcare has overlap between customers want and what is recognized by the professional opinion as need but resources are insufficient to meet that demand, then this can be seen for long waiting lists. In the middle of Figure 2, there is an area that represents the overlap between demand, need and supply. This is the care provided to patients that patients want and that is considered as effective by professionals. In this middle area, which spend of healthcare resources comes first is matter of efficiency. From research point of view all of these areas are challenging (Vissers 1998:79-80).

As people attempt to make decision for future events, they usually refer to past knowledge. All healthcare organizations need to predict the changing patient volumes and new consumer privilege, hard competition, constantly changing payer mix and shifting economic forces. They need to adjust plans, metrics and resource allocations in response to market and internal variability. Dynamic forecasting is required and needed.

Continual forecasting especially in healthcare organizations with multiple market pressures may need forecasting monthly or even weekly. Forecasting is the basic ground for decision making. Forecast serves its purpose by helping managers to make decisions about an uncertain future. Forecast errors can generate costs to the decision makers. Since forecast errors are essential in a random world, the classical theory of forecasting builds on the assumption that decision makers wish to cut down the expected cost associated to these errors. In literature organizations forecasters represent as the minimizers of the invisible expected cost (Engle 1982:988).

Healthcare business environment are data rich business areas which can cause problems. It is extremely important to choose the most relevant data; although, this is not always that straightforward. Healthcare organization can have multiple data for each service or function: the patient arrival time; the time when the medical treatment starts; the time of medical treatment completion. It is possible to model any of these data to generate healthcare service demand forecasts. Therefore it is important to understand the demand planning process and the customer requirements to select the most appropriate data. For example, planning may be based on when the healthcare demand arrives at the appointment system. From the patient's point of view, a more appropriate approach may have been to forecast the actual time of the demand occurrence (Voudouris et. al. 2008:57)

Revenue and expense forecasts can be tied to the payer mix, reimbursement rates and patient volumes by procedures, admissions or visits needed to generate a given strategic objective. Finance can provide managers with a useful model that includes information about past historical data realization and current headcount, as well as formulas driven by different assumptions. Healthcare managers can then make adjustments to this baseline on the basis of the latest business conditions. This approach also ensures collaboration across different functions in the organization.

Demand for healthcare leads to the demand for healthcare services. Forecasting demand for services makes up a ground for the healthcare organization's development. Healthcare organizations need accurate projections of the demand for the services that they are providing.

Modern research represents many quantitative forecasting methods for demand forecasting. Four most common methods of forecasting in healthcare environment are defined as percent adjustment, 12-month moving average, trend line, and seasonalized forecast. These four methods are all based for the organization's recent historical service data. (Murray et. al. 2004:53)

According to Murray et. al. (2004) there is many quantitative forecasting methods and models. Forecasting method or model should meet following criteria:
First, the necessary data should be easily available. Financial records typically represent the best source of historical data. The forecasting method should be able to use this data. Secondly, existing staff members should be equipped with easily available tools, such as spreadsheet software such as Microsoft Excel Add-ins or some selected statistical forecasting software like SPSS or PHstat, should be able to perform the internal forecasting. Thirdly, the forecasting method and its results should be

understandable not only for the financial management point of view but also to those who use the results for decision making (Murray et. al. 2004:53-54).

A critical aspect of the forecasting process is recognizing that forecasts based on historical data represent only the starting point for demand forecasting. Although demand for healthcare services is dynamic then in the short term, historical data can possibly provide the best forecast. Historical background data provides an opportunity to understand the different demand factors. Managerial decisions must be used in terms of both internal variables for example, changes in productivity and capacity and external variables for example, changes in demographics, healthcare demand patterns, technology, payment mechanisms, and competition.(Murray et. al. 2004:55)

Stark et. all (2008) suggests that for organization to establish the business need and clarify the demand forecast, the following key questions should be answered:

What decisions will the forecast influence?
Who are the key stakeholders?
What metrics are needed and how detailed should they be?
How far forward should the forecast project in terms of years, months, weeks, or days?
How will accuracy be measured, and what is the acceptable level of the error?
What is the impact of under- and overcasting? (Stark et.al. 2008:2-4).

In the discussion and conclusion section, this study provides an answer to these specified questions.

Figure 3 shows the effective forecasting of the demand for healthcare services, which requires nine steps:

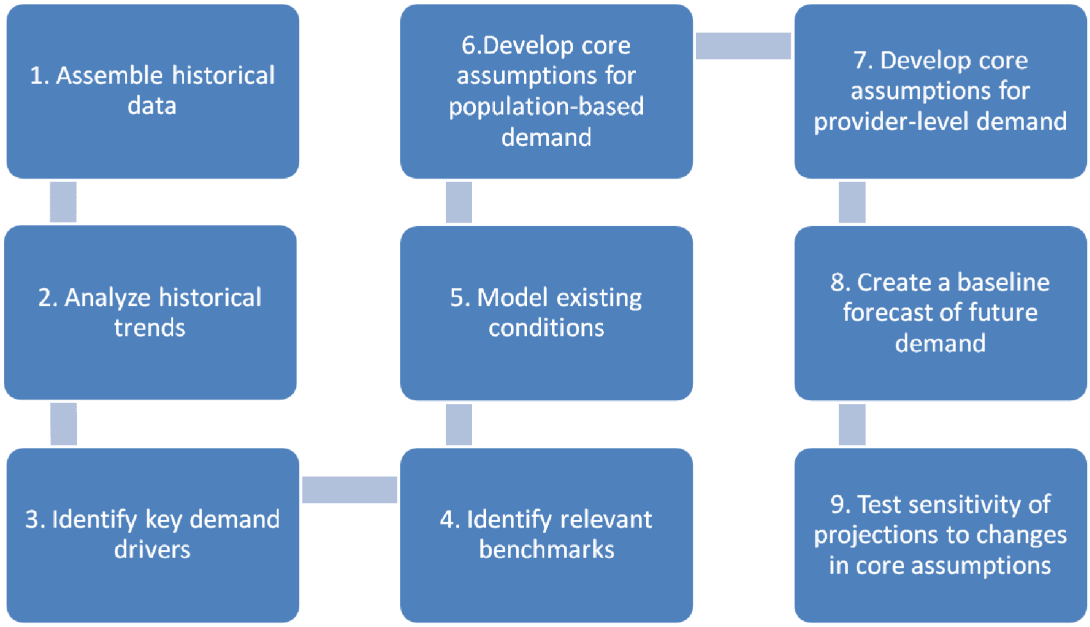


Figure 3. Drawing together these phases, effective forecasting of demand for healthcare services appears to require nine steps (Stark et.al 2008:2-4).

Figure 3 shows that organization has to assemble and analyze background data in the steps 1-4. After background data analyses organization have to develop core assumptions for population based demand and model existing conditions. When producing this analyses organization can create the baseline forecast of the future demand and build a forecasting model based on above mentioned steps.

2.1 Developing an Accurate Forecast

This subsection introduces the forecasting process and factors those effects for the forecasting. The forecasting process should fit to the special characteristics of the environment, and to the forecasting need of the healthcare organization. Chubb et. all (2010) concludes that the main focus for the healthcare forecasting research process is to design studies that will collect valid data. Forecasting models can contribute to the planning of a field study by assisting in the selection of a sampling strategy for example, models may identify certain population groups that should be preferentially recruited based on demographic characteristics or exposure history and in the estimation of the required sample size and during the study time. Models also help to clarify the assumptions that are built into a study's design. There is a feedback loop between field studies and models: data from field studies are used to create models that represent the real world, and models provide information about how to measure real-life variables (Chubb 2010:15).

Literature has concluded that successful demand forecasting has two fundamental objectives: to identify the key variables that grounds the demand for healthcare services within a selected service area; and to understand how and why these variables might change over time. Accomplishing these objectives requires a systematic analytical approach, which ensures that all aspects of potential demand are evaluated. Using nine-step process proposed by Stark et.al (2008) organization can create a database and framework for evaluating key variables and testing assumptions, and provide the necessary basis for accurately forecasting demand (Stark 2008:2-4).

There is no unique established way to describe the forecasting process. One of the key problems in developing an accurate forecasting process is how to separate the real time view of forecasting views. Forecasts are usually developed based on assumptions and static historical information, and the usual differences between actual demand and forecast demand can be easily misunderstood, resulting in attempts at fixing a non-existent problem. This can cause a chain reaction that can spread through the whole organization. (Finarelli 2004:55).

Dickersbach (2007) represent that the forecast model and its parameters have a significant impact on the quality of the forecast. To ensure the quality of the forecasting following process steps should be considered; ‘model evaluation’, ‘model selection’ and ‘parameter tuning’. If the performance of the forecast model exceeds the defined forecasting process step and the stability rules in the forecast profile allow changing the forecast strategy, an automatic model selection is performed and the forecast parameters are tuned. Forecasting process is a combination of these four process steps – model evaluation, model selection, parameter tuning and forecasting (Dickersbach 2007:64)

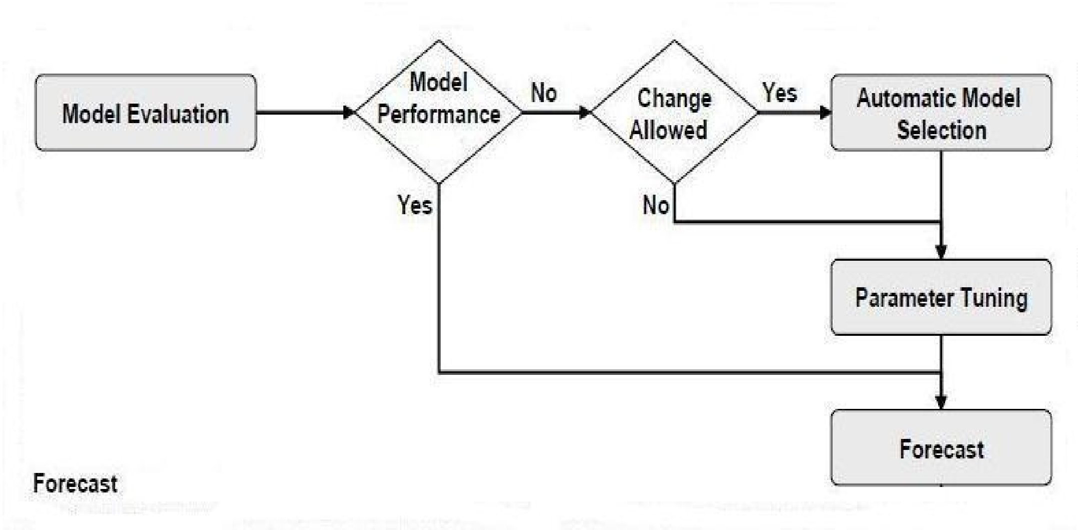


Figure 4. Process for forecasting (Dickersbach 2007:64).

Structured forecasting process may lead to a better understanding of the provided healthcare service (Dickersbach 2007:64).

Understanding the available historical data is the first step to start constructing forecasts. Without real knowledge of the historical data it is difficult to build any forecasting models. Healthcare data typically includes patient units of care, visit reason data, diagnosis data and visit time information, also laboratory and x-ray data might be included, in the model depending on what is the aim for forecasting. These data's should reflect the current and historical demand for the healthcare. The standard summary statistics, for example mean, standard deviation, are useful in providing a basic understanding of the data. For the decision makers and forecasters it is important to identifying appropriate amount of the data and to identify any general patterns. It is important to decide at the outset, what level of detail organization requires for the forecast. Inpatient utilization can be analyzed along several dimensions, including patient age, payer, product line (occupational healthcare services), major service or any combination for these dimensions. Data which is gathered should include and investigate both patient activity levels and throughput measures (such as average length of stay, visit duration, or procedure time) if service capacities (including numbers operating rooms, or treatment stations) need to be determined. This Thesis is concentrating on measurements and conditions that case organization conducts as healthcare service provider (Voudouris et. al. 2008:54-56).

One way to better understand the historical data is the use of scatter plots to identify possible correlation or non-linearity of the existing data. Time series graphs can indicate any patterns or unusual observations. When analyzing time series data there are four common patterns that observer should be aware of. Horizontal or stationary data fluctuate about a constant mean, trend: a long-term increase or decrease in the data, seasonal: a repeating pattern that depends on seasonal factors, for example days of the week, months of the year, cyclical: a recurring pattern that may have different length at irregular intervals (Voudouris et. al.2008:54-56).

Other types of data that healthcare organization has to investigate and take into consideration might include information about patient origin and market share by product line and geographic area, and emergency department visits by patient type for example admitted, fast-track, psychiatric and other types of patients and arrival time.

However, other type of data mentioned above is not so important for this Thesis, because the case organization patient population is in the Helsinki metropolitan area and, the case organization is not providing emergency services, only occupational services.

In literature is stated that administrative, financial and departmental data may sometimes vary significantly, because each of these areas collects and analyzes different statistics for different reasons. It has been said that many external databases have incomplete, inconsistent, or out of date information. It is therefore best to compare several data sources, if possible, to identify the most appropriate set of historical demand data (Finarelli 2004:50-70).

Organization have to examine at least three years of data to identify key trends which are an absolute change, a percentage change, and an average annual percentage change of the service data. This Thesis is using data between years 2008-2010 to construct the best possible forecast for the demand forecasting. Developing contacts between measures of the healthcare service demand may also be helpful for example, when studying admissions through the occupational services versus number of occupational service visits. Large changes in such ratios over a short time are unusual and may signal an underlying data problem. Changing data classification schemes should also be noted (Voudouris et. al. 2008:57-60).

Organization has to identify the key demand drivers. The key drivers of population-based demand include population growth and aging as well as changes in the technology or treatment patterns which affect specific service use rates. Other demand factors specific to a particular service, such as the substitution of insignificant procedures for certain types of medical treatment may also need to be identified and incorporated into the analysis (Finarelli 2004:50-70). In this Thesis aging and changes in the case organization workers´ working conditions are also considered when building a method for forecasting and analyzing the forecasting results.

Healthcare organization has to identify relevant benchmarks for forecasting processes. These benchmarks can provide the different reference for determining the demand trends in organization service area. Benchmarks need to be in line with wider marketplace or national trends in healthcare. Relevant benchmarks can include, use rates in comparative markets, established best practices or treatment protocols, or service-specific guidelines and performance measures.

Benchmarking opportunities include national or statewide databases; established best practices and protocols guidelines and performance measures published by know organizations. Medical journals that report results of clinical trials can be also considered as a benchmark. Web sites of recognized market leaders will provide potential sources for benchmarking. Also other researches may provide knowledge for organizations to start to implement forecasting process. (Finarelli 2004:50-70).

When starting to implement the forecasting process organization has to model existing conditions. For example, it may develop a spreadsheet model that best replicates the latest authenticated market data and market statistics. One difficulty is that the latest authenticated market data or market statistics for other providers may be more than a year old and not that easily available. Historical data and historical trends should be used to develop the most reasonable combination of assumptions about current conditions for the key demand drivers. If the model cannot replicate existing conditions, it cannot be used to predict future demand. (Tae et. al. 2009:1064).

Organization has to develop core assumptions for provider level demand. Factors that determine demand at the provider level include market share, patient mix or flow patterns, and operational performance. These factors are often called controllable factors because they can be affected by specific actions of the provider (Thomas 2003:55).

Using the most aggressive performance targets is considered as good business planning and tends to moderate the increase in resource requirements for example, staffing levels, facility capacity that might otherwise accompany projected increases in inpatient volumes. (Thomas 2003:54-60).

Healthcare organization has to develop core assumptions for population-based demand. Key factors affecting such demand include population growth, aging, and use rate and demographic profile including age mix. These factors are often called external factors, because they are outside of the healthcare organization's control. Organization can then use above mentioned nationwide databases and scientific medical publications. Occupational healthcare service providers often have better source of information about above mentioned customer data, because they know the population of the organization.

When organization is creating a baseline forecast of it future demand it has to take into consideration that forecast should combine the core assumptions for both population based and provider level demand. A baseline forecast includes reasonable assumptions for external factors such as population based demand, reasonable market share targets of the provider specific utilization levels and aggressive performance improvement of the baseline workload projections (Thomas 2003:54-60).

Organization has to consider alternative scenarios with different sets of assumptions. These kinds of scenarios might include low and high rates of change in population-based use rates. Results for this kind of changes, for non specific or specific reason, fall short when achieving projected operational efficiencies or other performance improvement targets. This helps organization to operate in different market situations. (Alho 1990:523-530).

It is useful to consider a best case scenario, with more promising assumptions, for example as higher population based demand, greater market share growth than were used in the baseline forecast. However it is probably more important for the organization to test the dark side of the sensitivity by using less promising assumptions about use rates, market share, or performance improvement (Finarelli 2004:50-70).

However it is not enough to simply project the historical trends regarding these population characteristics. Organization also must consider the factors that are causing demand to change and to hypothesize how these factors may change over time. Other factors that influence population based demand include medical practice patterns, structure of the service delivery system, and availability and design of insurance coverage (Alho 1990:523-530).

When healthcare organization is starting to forecast its demand for a given population it has to define the applicable geographic market or service area. The service area is most often expressed as a group of continuous zip codes, a single county, or multiple counties. In some applications, it is appropriate to define both a primary service area and a secondary service area. The appropriate definition of a service area may vary by service, even for the same service provider. (Thomas 2003:55-57). Service area of this Thesis is predefined as one selected business unit and its customers.

The age mix of the population is a key factor when organization is forecasting demand, as demand for healthcare services can vary dramatically by age. A population pyramid, also called an age structure diagram, shows the distribution of various age groups in a human population. It ideally forms the shape of a pyramid when the region is healthy. Population pyramid typically consists of two back-to-back bar graphs, with the population plotted on the X-axis and age on the Y-axis, one showing the number of males and one showing females in ten-year age groups. Males are conventionally shown on the left and females on the right.

Population projections can usually be obtained by age group as well as by geographic area. To capture the effect of age on demand, the demand model should be include at least four age groups (0-14,15-44, 45-64, and 65). In this Thesis age groups are between fewer than 30, 30-39, 40-49 and 50-59 and over 60. (Finarelli 2004:50-70).

Alho (1990) suggests that when multiplying the service area population of each age group by the expected use rate for a particular service, will tell the projected demand for that service, in that service area. Use rates are defined as a measure of health services utilization per 1,000 population (for example physician office visits per 1,000 population). Use rates can be determined from a variety of state and national databases, particularly for inpatient services and for many outpatient services. (Alho 1990:523-530).

Use rates can vary in geographic regions. Much of this variability can be attributed to the demographic profile of the population within the region, especially the age mix. (Alho 1990:523-530).

The relationship between age specific use rates and overall use rates tends to be the same in almost all market regions, regardless of the overall use rate for a given service. Finarelli (2004) proposes an example for the discharge rate for patients age 45 to 64 which is usually very close to the overall discharge rate for all ages and the discharge rate for persons age 65 and over is typically about three times the overall rate. Age specific discharge rates for any given market usually can be estimated once the overall rate for the market is determined. (Finarelli 2004:50-70).

Population based factors that concerns to the provider and its competitors service area also affect the demand and consumption of a provider's healthcare services. Major factors include competitive market position, configuration of services and facilities within the market, capacity constraints, operational efficiencies, and seasonal factors. These factors influence how many patients will use a specific provider as well as departmental workload levels. (Alho 1990 523-530).

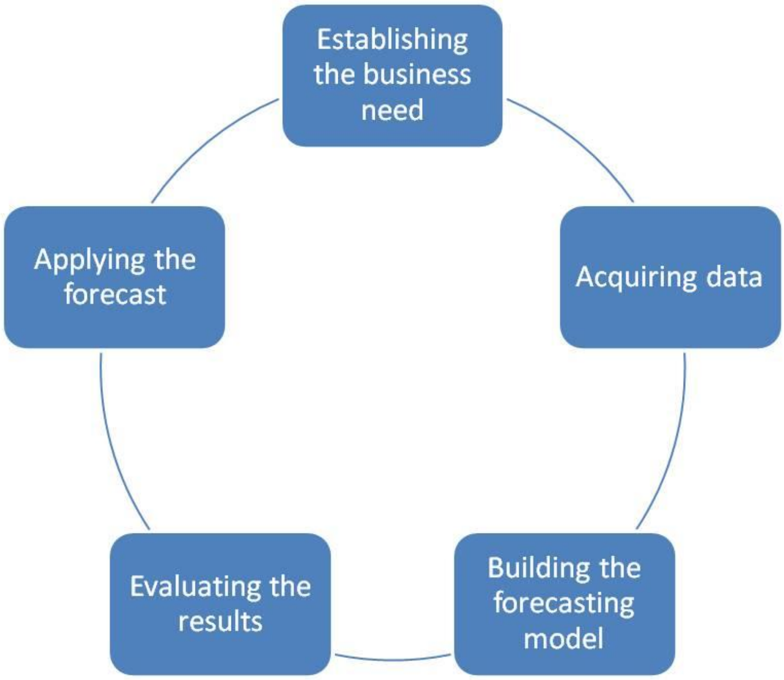


Figure 5. Major steps in the forecasting model (Stark et.al 2008:4).

By using different forecasting techniques, organizations can adjust the decisions that will help achieve their goals. The major steps that should be addressed in forecasting include the following methods which can be seen in Figure 5. Circle starts with established the business needs which organization has to decide before starting the forecasting process.

Key Revenue Drivers can be descripted as follows in Figure 6:

Figure 6. Key revenue drivers (Stark et.al. 2008:4).

These Key revenue drivers includes combination of the patient, physician and service center mix. Contracts between different parties' business office performance and volume walk hand in hand in the key revenue driver description. Seasonal changes for example spring time influenza wave will effect to the key revenue drivers. Target markets, new equipment schedules and utilization rates will provide different effects to the key revenue drivers. Healthcare organization has to recognize these seasonal factors because they give an impact for the actual forecasts.

Key Market and Strategic Business Influences can be illustrated in the Figure 7:

Figure 7. Key Market and strategic business influences (Stark et. al. 2008:5).

Above mentioned key market and strategic business common factors have to be taking into consideration when forecasting demand in the healthcare sector. (Stark et. al. 2008:5-6)

2.2 Forecasting Models

Previous sub-section represents the steps which organization has to take into consideration when constructing an accurate forecast. This sub-section discusses with different forecasting models.

The forecasting model and its parameters have a significant impact on the quality of the forecast. In general, there are two main types of forecasting methodologies. The scientific approach of statistical models based on historical data and the less mechanical approach using the judgement of experts. There are many different statistical methods, varying in complexity from relatively simple for example mean levels to sophisticated or computationally intensive techniques such as Autoregressive Integrated Moving Average (ARIMA). Judgmental forecasts are made by individuals based on their knowledge of the environment; this might include information about past events and expectations of likely future events or trends. Figure 8 Methodology tree for selecting forecasting approach collects together different kind of forecasting models and methods which are introduced through the literature. Statistical forecasting methods fall into two major families, those that utilize explanatory variables and those that use time series data. Judgmental forecasts, using techniques such as structured analogies can incorporate knowledge that does not exist in historic data, such as past events that are not expected to regenerate or expected future trends. (Voudouris et. al. 2008:57-60).

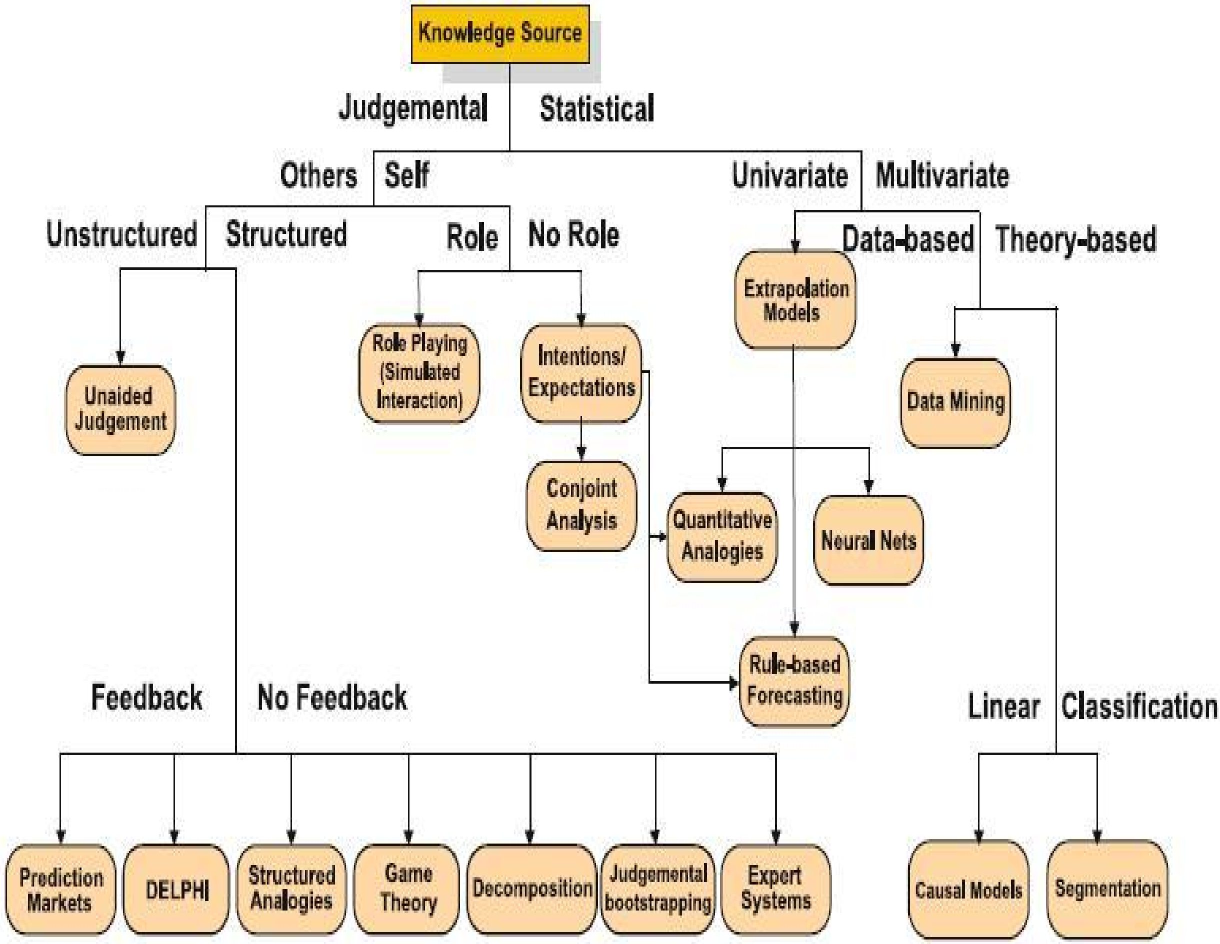


Figure 8. Methodology tree for selecting forecasting approach (Voudouris et. al. 2008:60).

The Different kind of advantages of both statistical and judgemental forecasting methods has led to the integration of the approaches in an attempt to optimize the forecasts.

The most important issue concerning the deployment of the forecasting models is their ability to generalize. Forecasting models have two important problem parameters that should be accounted for. The first is data preparation, which involves preprocessing and the selection of the most significant variables. The second embraces the determination of the optimum model structure (Sfetsos 2003:57).

Stark et. al. (2008) introduces three different kinds of models that can be used in healthcare forecasting. Cause and effect can be described as also known as causal model; assumes the factors that drive change will continue in the future. These factors are referred to as independent variables while the data to be forecast are referred to as the dependent variables. For example, changes in revenue are dependent on changes in payer mix and capacity.

Model can be used in multiple factors and long range forecasts such as revenue and patient volume (Stark et. al. 2008:7). Methods in this model can be seen in the Table 1.

Multivariate regression
Discriminant analysis
Decision trees
Factor analysis
Logarithmic regression

Table 1. Methods for cause and effect modeling (Stark et. al. 2008:7).

Time series analysis consists of methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Time series forecasting is used as a model to forecast future events based on known past events: to predict data points before they are measured. Time series forecasting assumes that variation in the revenue which occurred in the past time periods will continue to occur in the future. For time series models, the dependent variable is the forecasted metric, while the independent variable is time. These variables are clearly measured in forecasting software's for example in SPSS-statistics 19 which is one of the forecasting tools of this study.

Time series forecasting is used in short-range forecasts such as reimbursement rates. For example by using time series forecasting model can be seen in Table 2 (Stark et al. 2008:8).

- Exponential smoothing
- Box-Jenkins
- Autoregressive Integrated Moving Average (ARIMA)
- Decomposition

Table 2. Time series forecasting models (Stark et. al. 2008).

There are several advantages to using statistical methods. Statistical methods make efficient use of the available data; they are reliable for example two forecasts made with precisely the same input data will be identical; they are less flexible to personal bias and expert opinions. These methods can only interpret trends that are present in the data. (Voudouris et. al. 2008:57).

Judgement method is used in such as surveys, focus groups, and expert opinions for their predictions. Little or no historical data available, such as how new equipment purchase will affect inpatient and outpatient volume for a diagnosis related groups. Illustrations for this model can be seen in Table 3:

- Delphi
- Surveys
- Project Evaluation and Review Technique (PERT)

Table 3. Judgement method (Stark et. al. 2008).

Delphi surveys use with several individuals in isolation and then shares the results before the same individuals reforecast in the light of the shared information. Although

Delphi survey approach reduces assumptions, it can be time consuming and, that may not be appropriate way for short term forecasting (Voudouris et. al.2008:60).

Exploration based models are also used in forecasting such as Neural network forecasting which are model based methods. Neural networks models are data driven and self adjustable models. A neural network modeling is based on learning and predicting. Neural networks based models use generalizing techniques and models. Neural network models are good with non linear models and it can work well with sample data contain misjudged information. Forecasting models in general assumes that there is an underlying known or linear relationship between the inputs. Traditional statistical forecasting models algorithm have limitations in estimating underlying function due to the complexity of the real system. Neural networks models are often non linear. (Coskun et. al. 2009:3839-3844) This Thesis leaves the neural networks models for other researchers.

2.3 Forecasting Errors

Previous sub-sections have been introducing different forecasting methods. However, when using different demand forecasting models in service business and healthcare services business it is important to understand the constant error possibilities that different models might include.

In forecasting, a forecast error is the difference between the real and the forecasted value of a time series or any other phenomenon of interest. Error measures also play an important role in calibrating or redefining a model so that it will forecast accurately for a set of time series. In time series or statistical modeling the analyst may wish to examine the effects of using different parameters in an effort to improve a model (Armstrong et. al.1992:70).

Forecast may be assessed using the difference or using a relative error. In general the error is defined using the value of the outcome minus the value of the forecast. Different kind of error methods are used in forecasting error measurement such as Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE), Relative Absolute Error (RAE), Mean percentage error (MPE) Standard deviation of absolute percentage errors (SDAPE). A single series may dominate the analysis because it has a much larger or smaller error than that found for other time series. Listed error metrics measurements are opened up in Figure 9 (Armstrong et. al.1992:74-78).

Measure	Definition
Mean error	$ME = \frac{1}{n}\sum_{t=1}^{n} e_t$
Mean absolute error	$MAE = \frac{1}{n}\sum_{t=1}^{n} \lvert e_t \rvert$
Mean squared error	$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2$
Mean percentage error	$MPE = \frac{1}{n}\sum_{t=1}^{n} PE_t$
Mean absolute percentage error	$MAPE = \frac{1}{n}\sum_{t=1}^{n} \lvert PE_t \rvert$
Standard deviation of absolute percentage errors	$SDAPE = \sqrt{\frac{\sum_{t=1}^{n}(APE_t - \bar{APE})^2}{n-1}}$
Relative Absolute Error	$RAE_{m,h,s} = \frac{\lvert F_{m,h,s} - A_{h,s} \rvert}{\lvert F_{rw,h,s} - A_{h,s} \rvert}.$

Figure 9. Error methods in forecasting (Armstrong et. al.1992:78).

Forecast error may need to consider more general ways of assessing the match between the time profiles of the forecast and the outcome. If a main application of the forecast is to predict when certain service demand point will be crossed, one possible way of assessing the forecast is to use the timing error, the difference in time between when the outcome crosses the service demand point and when the forecast does so. (Voudouris et. al. 2008:63). R-squared method is used in this study to illustrates of how well a regression line approximates real data points; an r-squared of 1.0 (100%) indicates a perfect fit. In data analyzes part this study shows that R-squared and adjusted R-squared numbers are not supporting the linearity of the projection.

3 Research Method and Material

This Thesis has first introduced the findings from the literature, how healthcare organization should select the forecasting model and built the forecasting process. Current status analyses of the case business unit customers are introducing demographic information such as age profile of the selected customers group. Historical background data analysis has pointed out the fact, that OHCC has seasonal changes in the service provision. In the section 5 three different forecasting models are introduced and tested. Comparison is done with R-squared method which is introduced in this Thesis. Selected and proposed model is tested and compared with the actual service group event realization figures from the January and the February 2011. Management interviews were conducted after analysis and selection of the forecasting model. Management interviews consists the two managers of the selected business unit and the CEO of the OHCC. Discussion and conclusion part polishes the selected model.

This section describes the case study research method which is followed by the flow of this research. The second subsection introduces the used background data, which includes data interpretation of the Thesis. Second subsection describes the process for making appointments. Third subsection introduces the other research materials such as mathematical models and used forecasting tools and methods. The validity and reliability issues are discussed at the end.

3.1 Research Method

Case study is a method that focuses on understanding the dynamics in a context. Generally case studies are preferred, when “how” or “why” questions are to be answered (Yin 2009: 6). A case study is a research method common in social science. It is based on an in depth investigation of a single individual, group, or event. Case studies may be descriptive or explanatory. Case studies are considered as an appropriate research strategy particularly for new types of research areas where qualitative data is needed in the creation of proper understanding of the studied phenomena. Usually the first step in case study research is to determine and define the research question and then select the cases and determine the data gathering and analyzing techniques. Data is then collected, evaluated and analyzed.

This Thesis is conducted as case study method for selected business unit of Helsinki City Occupational HealthCare centre and its doctor's demand. Data interpretation is done IBM Cognos tools and forecasting is produced with Microsoft Excel spreadsheets and SPSS Statistics 19 analysis. The research strategy is quantitative.

In this Thesis, the case study research is based on mathematical modeling. The study relies on the mathematical model ARIMA (Autoregressive integrated moving average) applied in this research. In this Thesis the case study research is based on mathematical modeling. The study relies on the mathematical model ARIMA (Autoregressive integrated moving average) applied in this research. The ARIMA model has been selected for this Thesis based on past researches such as Milner 1988 (Milner 1988:1061-1076) Trent Region's Accident and Emergency (A&E) departments number of attendant in Emergency department. Milner introduced ARIMA model for forecasting attendant in Trent Region's Accident and Emergency departments. Farmer et. al 1990 (Farmer et. al. 1990:307–312) use ARIMA to predict the number of surgical beds required at the Charing Cross Hospital (Farmer et. al. 1990:307–312). Finarelli 2004 and Stark et. al. 2008 has introduced ARIMA model and other time series modeling used in health care sector (Finarelli 2004. Stark et. al. 2008).

3.2 Data Description

This research applies the concept of unit which has been used in the case organizations business unit and patient healthcare data for 2-4 years. Units of care are entered to OHCC data system by the doctors, who are providing the medical services for the customers. Data system, which OHCC is using, is provided with company called Acute FDs. Patient data system is called Acute (formerly TT2000+). Units of care examined in this Thesis are defined as status "Ready" –events. "Ready"-events are defined and used in the OHCC patient data system when medical staff is applying the units of care in the system and finishing their medical treatment sessions. Same patient system use invoiced unit as status "Invoiced"-units of care. These events do not consist the needed time data that this Thesis analyses. Units of care can be defined as short medical examinations 10-29 minutes, long medical examinations 30-90 minutes, phone call consultation or working condition examination which takes place in the working place. This Thesis introduces different time series data of the above specified care of unit groups.

3.3 Process for Making Appointments

In this subsection is described the process how the selected business unit confronts the demand on customers site. Healthcare processes can be classified as medical treatment processes or generic organizational processes. Medical treatment processes, are directly linked to the patient and are executed according to a diagnostic therapeutic cycle, comprising observation, reasoning and action. The diagnostic therapeutic cycle depends heavily on medical knowledge to deal with case specific decisions that are made by interpreting patient specific information. On the other hand, organizational or administrative processes are generic process patterns that support medical treatment processes in general. They are not tailored for a specific condition but aim to coordinate medical treatment among different people and organizational units. Patient scheduling and exam requests are two examples of organizational processes. Figure 10 illustrates the process for making reservation of the healthcare services.

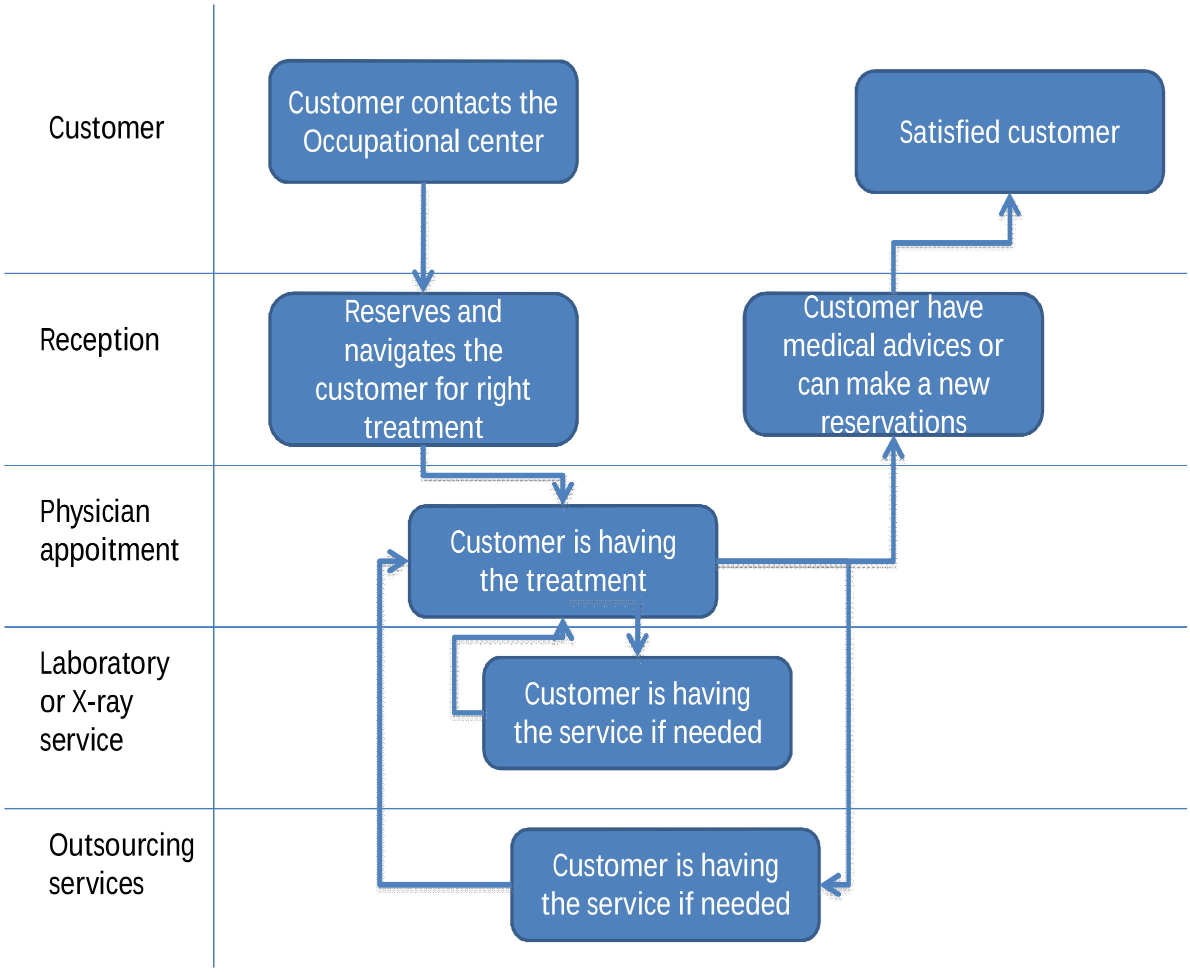


Figure 10. The current process for making reservation of the healthcare services.

At first customers have a need for the occupational healthcare services. Customers are approaching and contacting to the OHCC directly to the reservation desk or by using online appointment system or calling directly for their own nurse who will provide the first investigation of the nursing requirement. When customer is contacting directly for the reservation desk, operating staff will provide the first nursing requirement evaluation and gives a reservation time for a nurse or a doctor. Process suggests first nurse's appointment and secondly if the need for a doctor is immediate then reservation desk personnel will reserve the time for the doctor directly. When customer is in the nurse's appointment and there is need for doctor's appointment and there are no available times for the team doctor, nurse will give the obligation to use the outsourcing services. Same outsourcing services are used if doctor decides that there is need for some other special treatment which cannot be provided in-house. Otherwise nurses or doctor's appointment will lead to the other medical investigations in-house for example laboratory services and X-ray services.

This Thesis investigates and builds the model which will help business unit management team to plan and forecast the healthcare demand of the selected business unit doctors. Figure 11 illustrates customer's process.

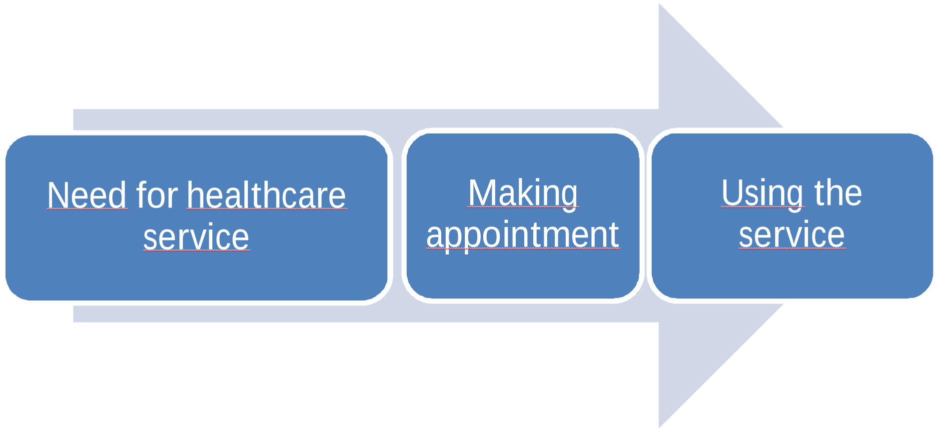


Figure 11. Process for customer using the occupational healthcare service.

Interviews which are conducted in this Thesis are done with the head of the selected business unit, after producing the forecast with the selected forecasting tool. Forecasting results are analyzed with line management. Top management interviews are also conducted to evaluate the forecasting results. Interviews main purpose is to validate the forecasting outcomes with the knowledge of the line management. Interview questions are concerning the historical data analyses and questions about staff resourcing during the holiday seasons and in high seasons. Forecasting results are compared and discussed with line and top management

Criteria for the quality of case study in this Thesis can be seen in use of existing patient data and using top and line management suggestions to identify the common variables for the demand forecasting model.

Internal validity in this Thesis is done with pattern matching technique and logic model analyses with using existing mathematical models such as ARMA, ARIMA, SARIMA and SPSS expert modeler which is modification of ARIMA and Exponential Smoothing models and it takes into consideration seasonal variation of the data. Three different models are analyzed to create and guarantee the validity of the models. Also disclosure of errors is used to guarantee the validity of the forecasting factors. Above in this section are introduced the three different forecasting tools.

External validity in this Thesis is recognized in the literature where in other research studies have used similar mathematical models in predicting the demand of the healthcare services. (Yin 2009:34-39).

Research techniques that are used in this Thesis are following:

- Statistical analysis of the existing patient database.
- Constructing the actual forecasting model.
- Data which is used in the model is analyzed with top and line management interviews.
- Validating and comparing the results.
- Forecasting interpretation is conducted whit top management and line managers.

The process for this case study is described in Figure 12 demand forecasting process:

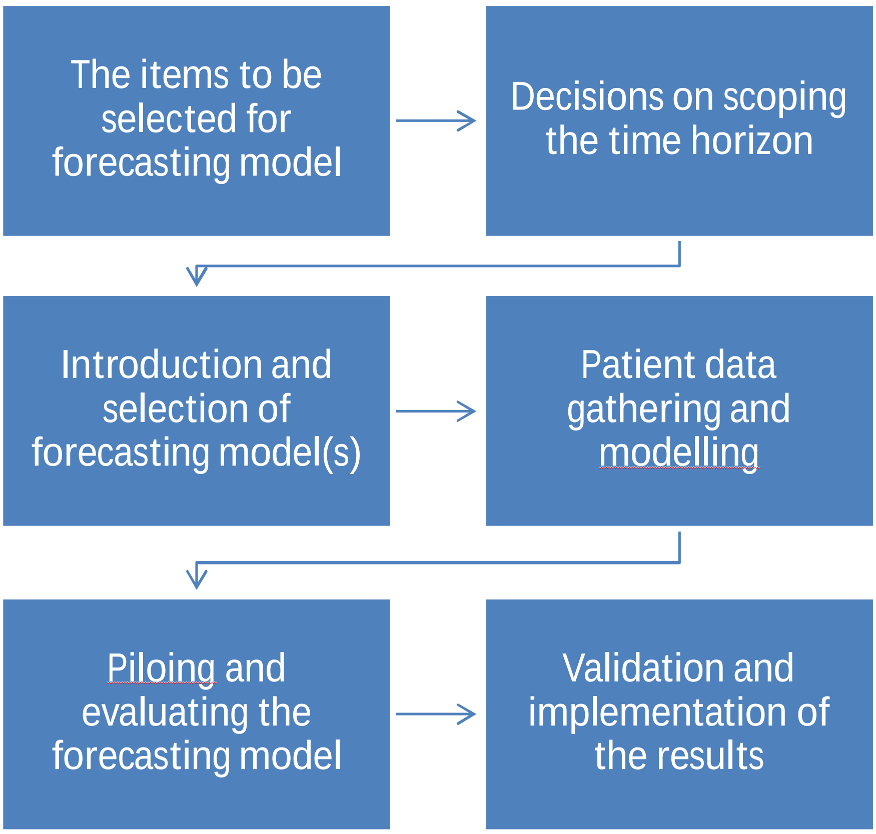


Figure 12. Demand forecasting process.

3.4 Research Material

Forecasting material can be defined as the historical data and human resource data. Forecasting tools which are introduced in this Thesis, such as Microsoft ARMA Add-in and SPSS statistics 19 are providing the tool for this study's model. Other sources of materials are shown as graphs and figures based on the use of the forecasting tools and based on the Occupational data mining which are conducted with by using Cognos BI 8.3 tools.

3.4.1 Background for the Forecasting Tools

This section describes the mathematical background of the forecasting tools analyzed in this Thesis.
Other researcher in healthcare forecasting has been using ARIMA model as demand forecasting tool. Milner PC (Milner 1988:1061-1076) describes an ARIMA model that predicts the annual number of attendances at Trent Region's Accident and Emergency (A&E) departments. Milner evaluated the accuracy of his earlier forecasts with generally favorable results and recommend that ARIMA modeling for to be registered fully into planning at health district levels. Farmer et al (Farmer et. al. 1990:307–312) used ARIMA to predict the number of surgical beds required at the Charing Cross Hospital (Farmer et. al. 1990:307–312). Gilchrist describes the use of queuing theory to estimate hospital bed requirements with ARIMA model (Gilchrist 1985:206). Research mentioned above has mainly concerned with identifying the strategic service requirements.

This Thesis investigates mathematical models which are relevant in the literature to conduct time series forecasting in accurate way. Autoregressive Integrated Moving Average ARIMA model is introduced here as a one relevant case study model. Autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. Time series forecasting methods are more appropriate for short term forecast which are applied for this study.

The ARMA model consists of two basic load components, a deterministic and a stochastic component. The first parameter stands for the periodic part of the load shape, while the second parameter points out the deviation of the random effects. The deterministic component is given by a time dependent periodic nonlinear function, and the stochastic one is represented by an ARMA model if the underlying stochastic process is stationary with limited variance, or an ARIMA (autoregressive integrated moving average) model if the underlying stochastic process is non-stationary. (Tzafestas et. al.2001:10)

Auto regressive integrated moving average (ARIMA) models intend to describe the current behavior of variables in terms of linear relationships with their past values. These models are also called Box-Jenkins (1984) models on the basis of these authors' pioneering work regarding time series forecasting techniques. An ARIMA model can be decomposed in two parts. First, it has an Integrated (I) component (d), which represents the amount of differencing to be performed on the series to make it stationary. The second component of an ARIMA consists of an ARMA model for the series rendered stationary through differentiation.

This model type is generally referred to as ARIMA(p,d,q), with the integers referring to the autoregressive, integrated and moving average parts of the data set, respectively. ARIMA modeling can take into account trends, seasonality, cycles, errors and non-stationary aspects of a data set when making forecasts.

These models are fitted to time series data either to better understand the data or to predict future points in the forecasting. Models are applied and conducted in some cases where data shows evidence of non stationary demand, where an initial differencing step corresponding to the integrated part of the model can be applied to remove the non-stationary model.

The ARIMA(p,d,q) model where p, d, and q are non-negative integers that refer to the order of the autoregressive, integrated, and moving average parts of the model. When one of the terms is zero, it's usual to drop AR, I or MA. For example, an I(1) model is ARIMA(0,1,0), and a MA(1) model is ARIMA(0,0,1).

Definition of the model can be conducted as follows: Given a time series of data Xt where t is an integer index and the Xt are real numbers, then an ARMA(p,q) model is given by

$$\left(1-\sum_{i=1}^{p}\alpha_i L^i\right) X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right) \varepsilon_t$$

where L is the lag operator, the αi are the parameters of the autoregressive part of the model, the θi are the parameters of the moving average part and the \varepsilon_t are error terms. The error terms \varepsilon_t are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean. (Mills et. al.1991:116-120)

ARIMA models are used for observable non-stationary processes Xt that have some clearly identifiable trends:
Constant trend for example a non-zero average leads to d = 1
Linear trend for example a linear growth behavior leads to d = 2
Quadratic trend for example a quadratic growth behavior leads to d = 3
In these cases the ARIMA model can be viewed as a cascade of two models. The first is non-stationary:

$$Y_t = (1-L)^d X_t$$

While the second is wide sense stationary:
(Mills et. al.1991:116-120)

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right) Y_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right) \varepsilon_t \,.$$

The numbers of variations on the ARIMA model are commonly used in literature. For example, if multiple time series are used then the Xt can be thought of as vectors and a VARIMA model may be appropriate. Sometimes a seasonal effect is suspected in the model. For example model of daily road traffic volumes. Weekends clearly exhibit different behavior from weekdays. In this case it is often considered better to use a SARIMA (seasonal ARIMA) model than to increase the order of the AR or MA parts of the model. If the time series is suspected to exhibit long range dependence then the d parameter may be replaced by certain non-integer values in an autoregressive fractionally integrated moving average model, which is also called a Fractional ARIMA (FARIMA or ARFIMA) model (Mills et. al. 1991:116-120).

ARIMA models such as those described above are easy to implement on a spreadsheet. The prediction equation is simply a linear equation that refers to past values of original time series and past values of the errors. Researcher can set up an ARIMA forecasting spreadsheet by storing the data in column A, the forecasting formula in column B, and the errors (data minus forecasts) in column C. The forecasting formula in a typical cell in column B would simply be a linear expression referring to values in preceding rows of columns A and C, multiplied by the appropriate AR or MA coefficients stored in cells elsewhere on the spreadsheet (Mills et. al. 1991:116-120).

In this Thesis ARIMA-model is build in to the IBM Cognos planning tool to formulate the demand. SPSS Statistics 19 is used to model the forecast figures. Comparison of the tools is done with using Microsoft excel add-in.

3.4.2 Forecasting Tools

This subsection introduces the three forecasting tools which are used in this study.
First tool for the forecasting model is based on Microsoft Excel Add-in. The tools is develop to use ARMA model as ARIMA(p,d,q) where p=timeseries d=integers d and integers q. The following time series functions are used in the model. The output will be a range of the specified forecasting period in moths.

`diff(time series as range, d as integer)`	d'th order difference
`difflog(time series, d as integer)`	d'th order difference of the logarithm
`diffs(time series as range, d as integer, s as integer)`	d'th order difference with a seasonal difference s
`diffslog(time series as range, d as integer, s as integer)`	d'th order difference with a seasonal difference s of the logarithm

Figure 12. Microsoft excel variables in forecasting tool.

Microsoft Excel Add-in model estimates the parameters of an ARMA(p,q) model. ARMA needs as parameters a time series as a range, the order of autoregressive terms q as integer, the order of moving average terms q as integer, and an constant term into the model an boolean as true. After estimating this functions returns the residual, the parameters, useful statistics, impulse response function and forecast evolution in a range of the size $(T - p) \times \max(p + q + c, 3)$. The first parameter will be outputted in column 2 and row 1. The orders of parameter are constant, autoregressive parameters and moving average parameters. The estimation employs an efficient nonlinear technique (Levenberq Marquardt algorithm).

Second forecasting tool is SPSS-statistics 19.0. SPSS statistics 19.0 is selected therefore that it can produce Seasonal ARIMA models. Historical data analyses in Section 4 will shown the seasonality of the provided occupational healthcare services and that gives a reason to assume that SARIMA model can work in practice.

In SARIMA model all variables must be non negative integers. For autoregressive and moving average components, the value represents the maximum order. All positive lower orders will be included in the model. Seasonality is enabled if a periodicity has been defined for the active dataset Autoregressive (p). Autoregressive orders specify which previous values from the series are used to predict current values. For example, an autoregressive order of two specifies that the value of the series two time periods in the past be used to predict the current value. Difference (d) specifies the order of differencing applied to the series before estimating models. Differencing is necessary when trends are present (series with trends are typically nonstationary and ARIMA modeling assumes stationarity) and is used to remove their effect. Moving Average (q) specify deviations from the series mean for previous values are used to predict current values.

Seasonal autoregressive, moving average, and differencing components play the same roles as their non seasonal counterparts. For seasonal orders, current series values are affected by previous series values separated by one or more seasonal periods. Following parameters are used in the forecast:

```
PREDICT THRU END.
* Time Series Modeler.
TSMODEL
  /MODELSUMMARY  PRINT=[MODELFIT RESIDACF] PLOT=[ SRSQUARE RSQUARE RMSE MAPE MAE MAXAPE MAXAE NORMBIC RESIDACF RESIDPACF]
  /MODELSTATISTICS  DISPLAY=YES MODELFIT=[ SRSQUARE RSQUARE RMSE MAPE MAE MAXAPE MAXAE]
  /MODELDETAILS  PRINT=[ FORECASTS]
  /SERIESPLOT OBSERVED FORECAST
  /OUTPUTFILTER DISPLAY=ALLMODELS
  /AUXILIARY  CILEVEL=95 MAXACFLAGS=24
  /MISSING USERMISSING=EXCLUDE
  /MODEL DEPENDENT=Short_examinations Long_examinations Working_conditions Phone_calls Total INDEPENDENT=YEAR_ MONTH_
    PREFIX='Model'
  /ARIMA AR=[0]  DIFF=0  MA=[0]  ARSEASONAL=[1]  DIFFSEASONAL=0  MASEASONAL=[1]
    TRANSFORM=NONE  CONSTANT=NO
  /AUTOOUTLIER DETECT=OFF.
```

Figure 13. Parameters for SPSS SARIMA forecasting method.

Other factors such as goodness of fit shows summary statistics and percentiles for following metrics; stationary R-square, R-square, root mean square error, mean absolute percentage error, mean absolute error, maximum absolute percentage error, maximum absolute error, and normalized Bayesian Information Criterion.

Residual autocorrelation function (ACF) summaries statistics and percentiles for autocorrelations of the residuals across all estimated models. Parameter estimates displays a table of parameter estimates for each estimated model. If outliers exist, parameter estimates for them are also displayed. Residual autocorrelation function (ACF) displays the lag for each estimated model. Residual autocorrelation function includes the confidence intervals for the autocorrelations. Residual partial autocorrelation function (PACF), displays by lag for each estimated model. The table includes the confidence intervals for the partial autocorrelations.

Third forecasting tool is SPSS-statistics 19.0 and it expert modeler. Expert Modeler considers both seasonal and non seasonal time series models. Expert modeler uses same variables that introduced in the SARIMA model but it combines the background data for both exponential smoothing and ARIMA model forecast. Variables which are used in the model can see in Figure 14.

```
PREDICT THRU END.
* Time Series Modeler.
TSMODEL
  /MODELSUMMARY  PRINT=[MODELFIT RESIDACF]
  /MODELSTATISTICS  DISPLAY=YES MODELFIT=[ SRSQUARE RSQUARE RMSE MAPE MAE MAXAPE MAXAE NORMBIC]
  /MODELDETAILS  PRINT=[ FORECASTS]
  /SERIESPLOT OBSERVED FORECAST
  /OUTPUTFILTER DISPLAY=ALLMODELS
  /AUXILIARY  CILEVEL=95 MAXACFLAGS=24
  /MISSING USERMISSING=EXCLUDE
  /MODEL DEPENDENT=Short_examinations Long_examinations Working_conditions Phone_calls Total INDEPENDENT=YEAR_ MONTH_
    PREFIX='Model'
  /EXPERTMODELER TYPE=[ARIMA EXSMOOTH] TRYSEASONAL=YES
  /AUTOOUTLIER  DETECT=OFF.
```

Figure 14.Parameters for SPSS expert model forecasting method.

Each model will represent the forecasting results are compared between above described forecasting tools.

3.5 Validity and Reliability

Quantitative research designs are either descriptive or experimental. A descriptive study establishes only associations between variables. An experiment establishes causality. Quantitative research is all about quantifying relationships between variables. Variables can be weight, performance, time, and treatment. In this study a combination of literature investigations, interviews, creating data sets and data mining and the researcher's narrow training in specific fields set limits. The researcher in this study is a Bachelor of Science in Industrial management with four years of work experience in the case company, in as IT-designer and modeling usability reports for top-management. In the forecasting model selection process, three individual forecasting methods are tested and analyzed for securing the validity and reliability of this Thesis. Literature review suggests that better and more reliable forecasts can be performed if there is comparison between different forecasting methods.

4 Current State Analysis

This section analyses the present healthcare service state of the case organization. Analyses are conducted with healthcare data mining with Cognos BI 8.3 tools. Also demographic variables such as age are discussed.

Present state in the case organization is that there is no functioning model for demand forecasting. Organization has set goals and targets for the nursing staff (doctors, nurses, physiotherapists and psychologies). Their goals are only representing the targets for each professional group, which they should reach in monthly level. These targets are discussed and defined based on previous year outcome of the provided services as classified in the four main categories. These are introduced in the research method and material section.

This Thesis discusses and analyses the model for one business unit of the case organization and its customers. Forecasting the demand of this target customer group will give management tools for the case business unit leaders to define the predicted workload and, predicted healthcare service need for the case organizations population. Key stakeholders are the business unit leaders and top management of the organization. Other stakeholders are development team and case customer organization top management. Forecasting metrics are 2-4 years of patient data; human resource data such as age are used for the background analysis.

Forecasting model applies tool for case organization workload planning and investigating the seasonal factors and preparations and planning for the staff holidays.

This Thesis applies the questions that how demand forecasting can influence the prediction and usage of the rented doctors and physicians. Forecasting model tries to find the answer for the actual needs and planning how to use in-house rented doctor services.

4.1 Case Customer Population

Sub-section 4.1 introduces and analyses customer population of the case business unit customers. Case unit has 9100 customers (year 2009) whose demand for healthcare services is analyzed in this Thesis. Case unit customers permanent average age was in the year 2009 46,3 years. The proportion of women was 90,3%.

Following tables illustrates and analyzes the age and other factors of the case organization. Figures are collected from the annual Helsinki city analyze from the year 2010 (Talous ja Suunnittelukeskus 2010:5-20).

Organization	Permanent staff Avarage age			Temporary staff Avarage age		
	Men	Women	Outcome	Men	Women	Outcome
	45,4	46,4	46,3	34,7	36,3	36,1

Table 4. Average age statistics of the case organizations customers.

Table four illustrates the average age of the case organizations permanent and temporary staff members. Permanent staff members average age was in the year 2009 46,3 and in the permanent staff 36,1 years. Women's average age was bit higher (46,4 years) than men's corresponding figure (45,4) (Talous ja Suunnittelukeskus 2010:5-20).

Over 54 years %		Over 54 years in numbers		Permenent staff in numbers	
Men	Women	Men	Women	Men	Women
17,3	24,7	153	2029	882	8223

Table 5. Age statistics of the case organization.

Case organization staff members age distribution table shows that in the year 2009 organization had over 54 years old staff members 17,3 percents men and 24,7 percents women. Total numbers of the over 54 years old were 153 men and 2029 women.

Permanent staff age differentiation 2009									
Age groups									
under 30	%	30-39	%	40-49	%	50-59		60 and over	
609	8,5	1433	19,9	2164	30	2361	32,8	635	8,8

Table 6. Permanent staff age differentiation.

Age differentiation in the case organization is illustrated in the Table 6. The largest group is 50-59 years and the second largest group is 40-49 years. Largest occupational healthcare need is estimated to be in the group 50-59; however that is also the largest customer group in the case organization (Talous ja Suunnittelukeskus 2010:5-20).

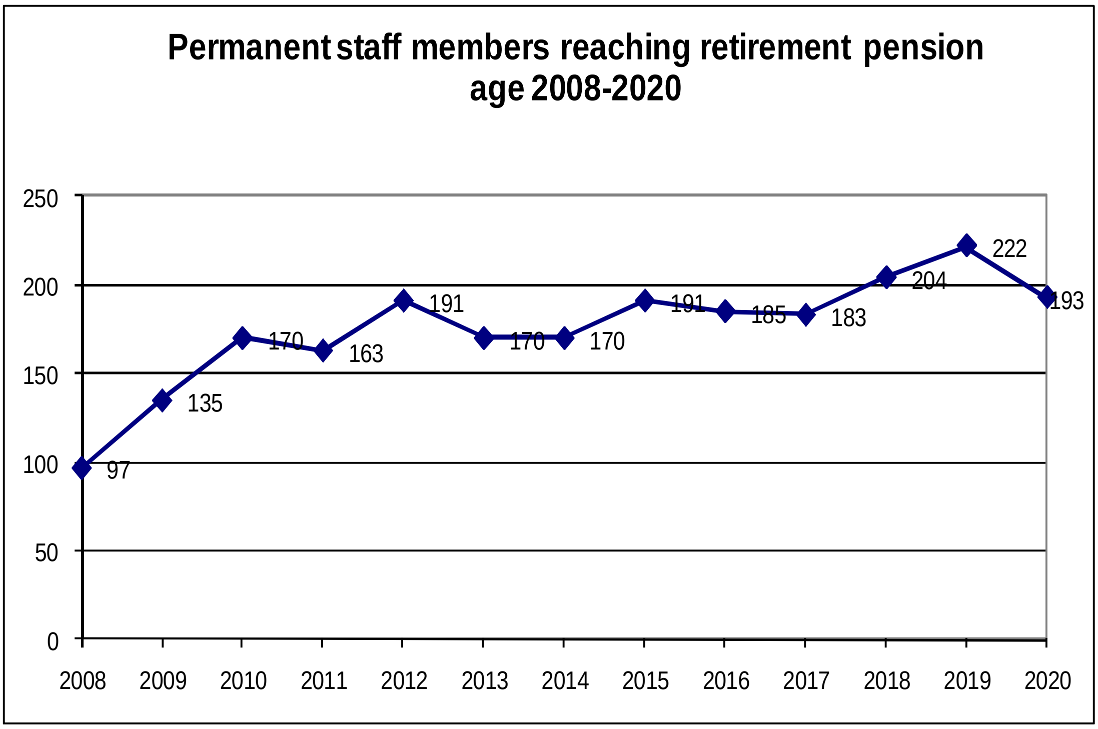


Figure 15. Permanent staff members' reaching retirement pension age 2008-2020.

Figure 15 illustrates the permanent staff members reaching the retirement pension in the following years till 2020. Figure 15 provides information about staff member's retirement pension age between years 2008-2020.

4.2 Analyzing the Demand for the Case Unit

This sub-section analysis is based on the provision of the medical services for the case organizations. Case organization healthcare provider team consists of the 9 doctors and 9 nurses. This Thesis concentrates and analyses demand on the doctor's point of view. When analyzing the customer data in the three year time line we can see that there are three peak seasons in the customer demand. Figures are calculated for overall customer demand for the doctors which consist following services: short and long medical examination, telephone calls or working conditions examinations which are conducted with doctors.

In this sub-section is analyzed the historical data of the selected business unit. Historical patient data will construct the base for the forecasting model. First this Thesis analyses the historical overall trends and gives suggestions for the forecasting model.

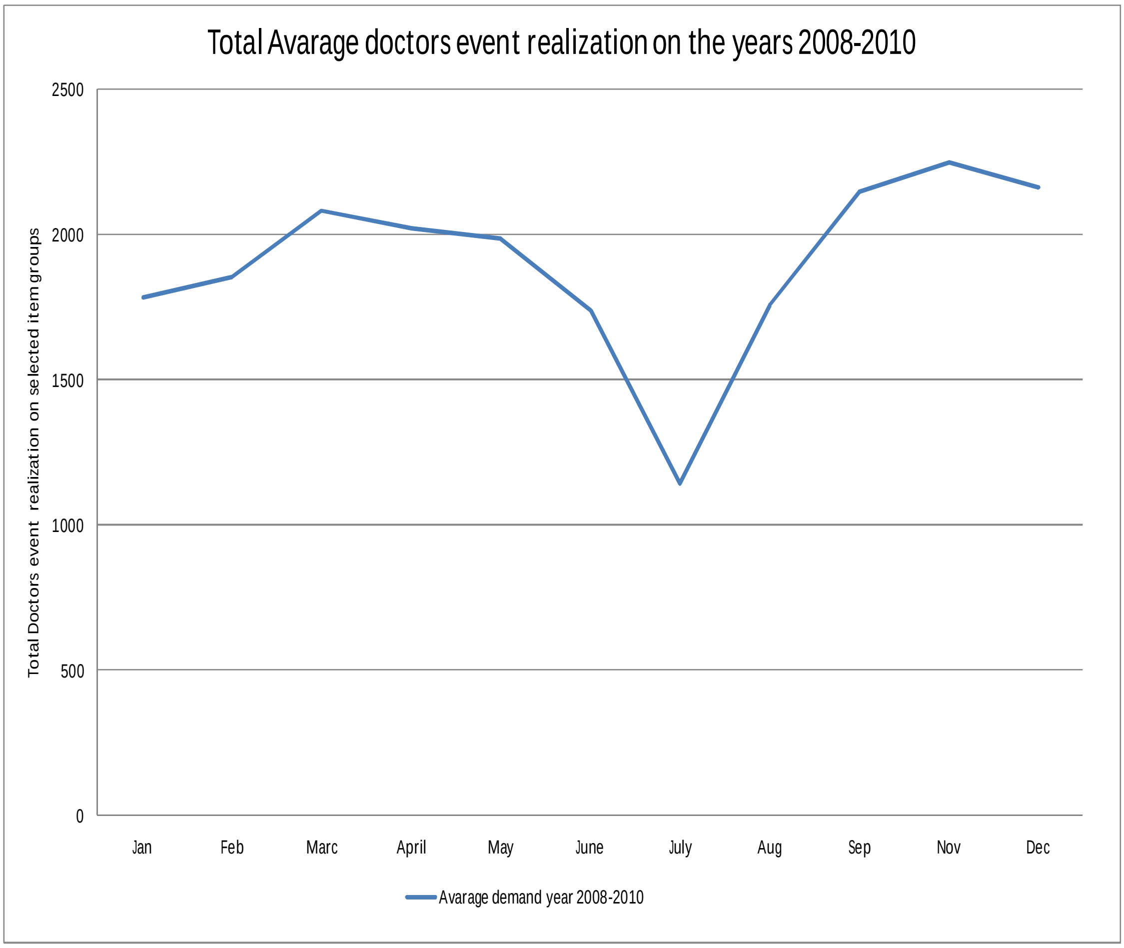


Figure 17. Total average of the selected doctor's events realization.

Figure 17 gives total average numbers for the selected business unit doctors realized event groups. Average numbers between 2008-2010 gives an overview for the sesonal effects of the occupational healthcare demand. High seasons seems to be in the spring in March, April and May and in the fall and during the winter time the largest demand peak seasons are in September, October and November. It is apparent that there is a seasonal variation for both series. Seasonal variation seems to be both at a maximum during the winter months and before the summer months. Weekly seasonal effects can also be observed.

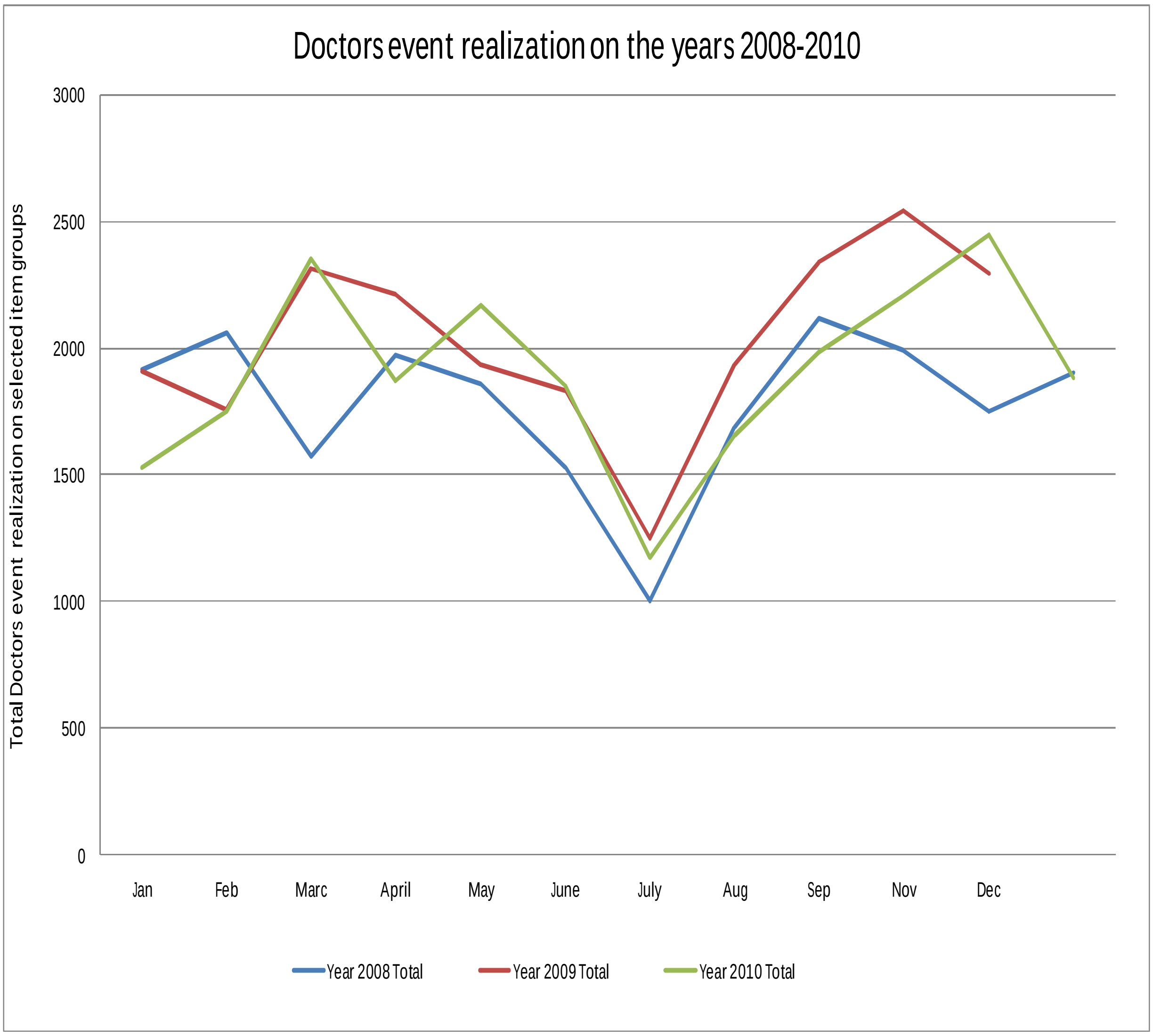
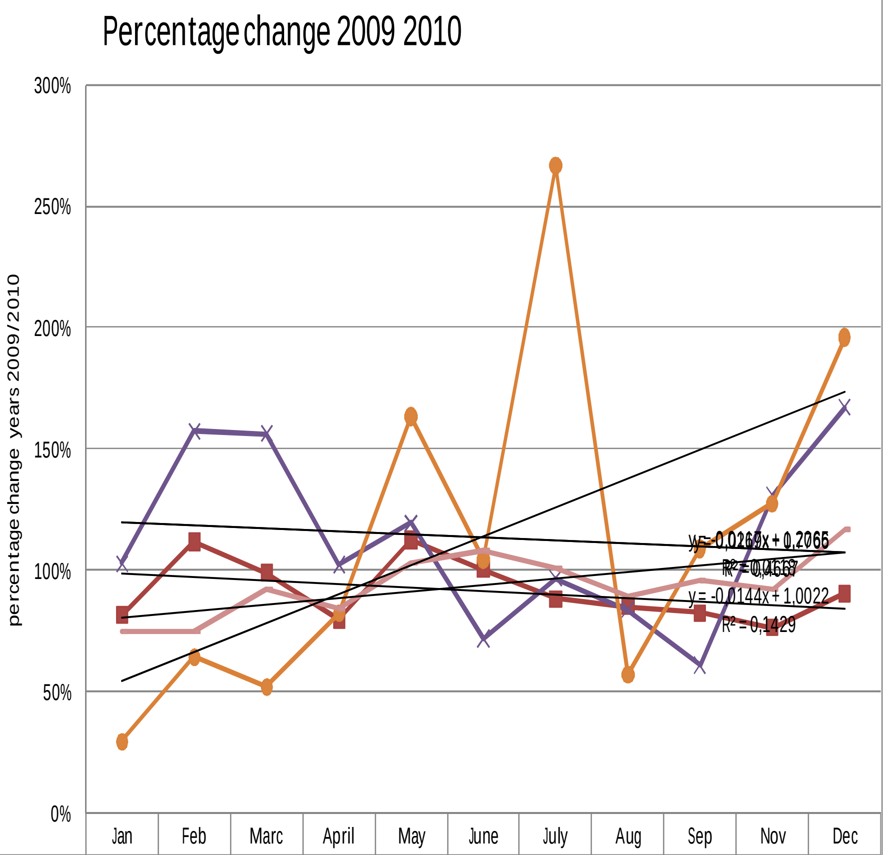


Figure 18. Doctors event realization on the years 2008-2010.

Figure 18 illustrates the total event realization in individual numbers for the years 2008-2010. There seems to be changes between the investigated years in the monthly level. However the seasonal variation seems to be guite similar for each individual time series.



	Jan	Feb	Marc	April	May	June	July	Aug	Sep	Nov	Dec
Percentage change 2009/2010Short medical examination	81%	112%	99%	80%	113%	100%	88%	85%	82%	77%	91%
Percentage change 2009/2010 Long medical examination	103%	157%	156%	102%	120%	72%	97%	84%	61%	131%	167%
Percentage change 2009/2010 Working conditions examinations	30%	64%	52%	82%	163%	105%	267%	57%	109%	128%	196%
Percentage change 2009/2010 Telephone calls	75%	75%	92%	84%	103%	108%	101%	89%	96%	92%	117%

Figure 19. Percentage change 2009-2010.

Figure 19 illustrates percentage change between years 2009-2010. When analyzing the linear regression curve, overall change seems to be quite stabile and growing when looking at the percentage change between the different units of care group series.

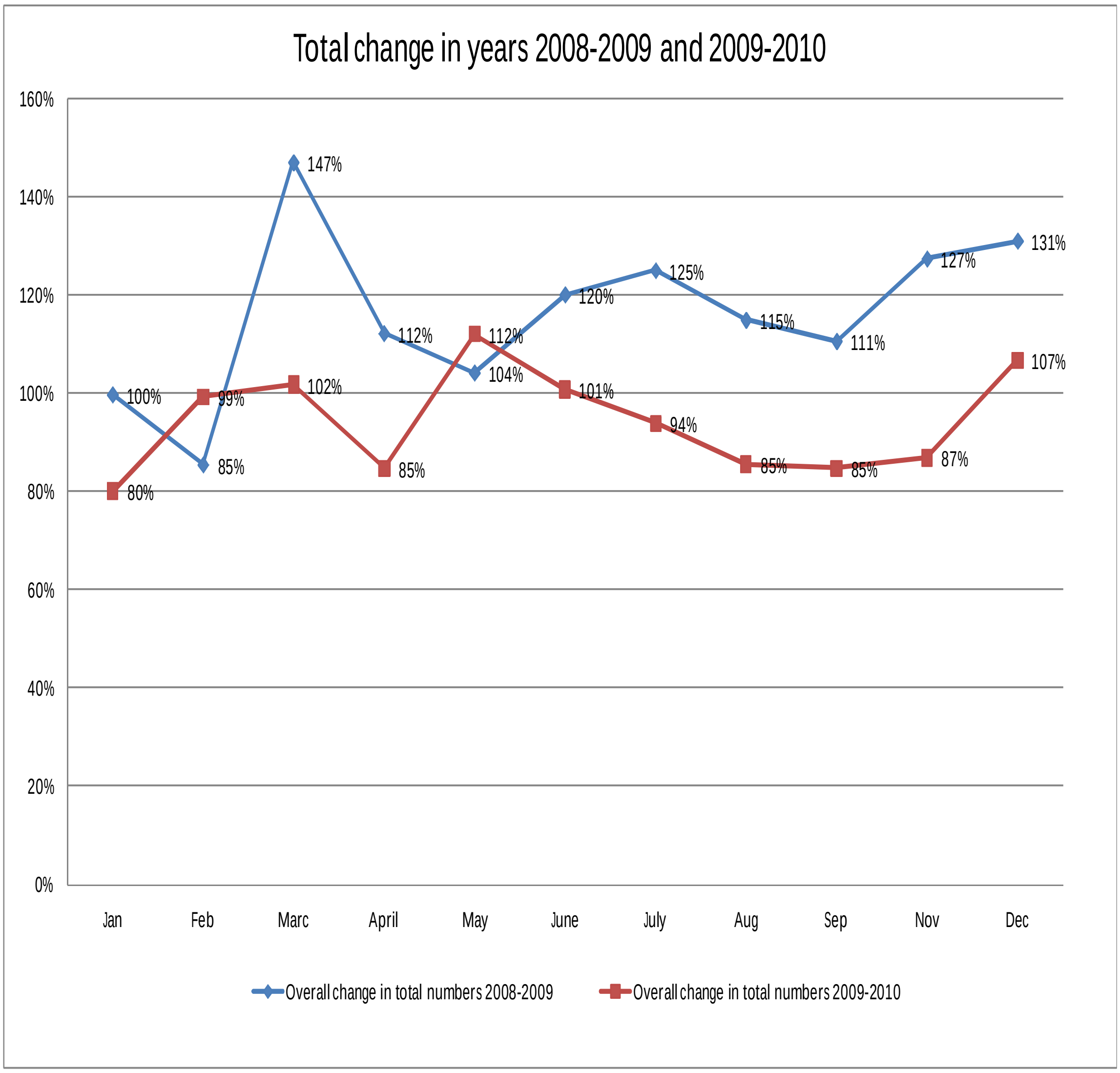


Figure 20. Total change in years 2008-2009 and 2009-2010.

Figure 20 illustrates the total overall change in the doctor's visits of the selected caring service groups in the years 2008-2009 and years 2009-2010. Analyzing and comparing the figures between the years the largest change was in the year 2009. This change can also be result from the lack of resources in the year 2008 and 2010 in the some moths. Figure shows that total change of the selected caring service groups are meeting quite large change if we compare results between different years.

4.3 Analyzing Monthly and Weekly Demand

This sub-section analyses monthly and weekly total visits of the selected business unit. The purpose for this analyze is to clarify and construct the base for making monthly and weekly demand analyses for the case business unit. Literature has also pointed out the importance of the historical background analyzes for the forecasting process. Following month and week based analyses are investigated on average data of March therefore at March seems to be one of the crowded months, when analyzing at the Figure 17 or Figure 18.

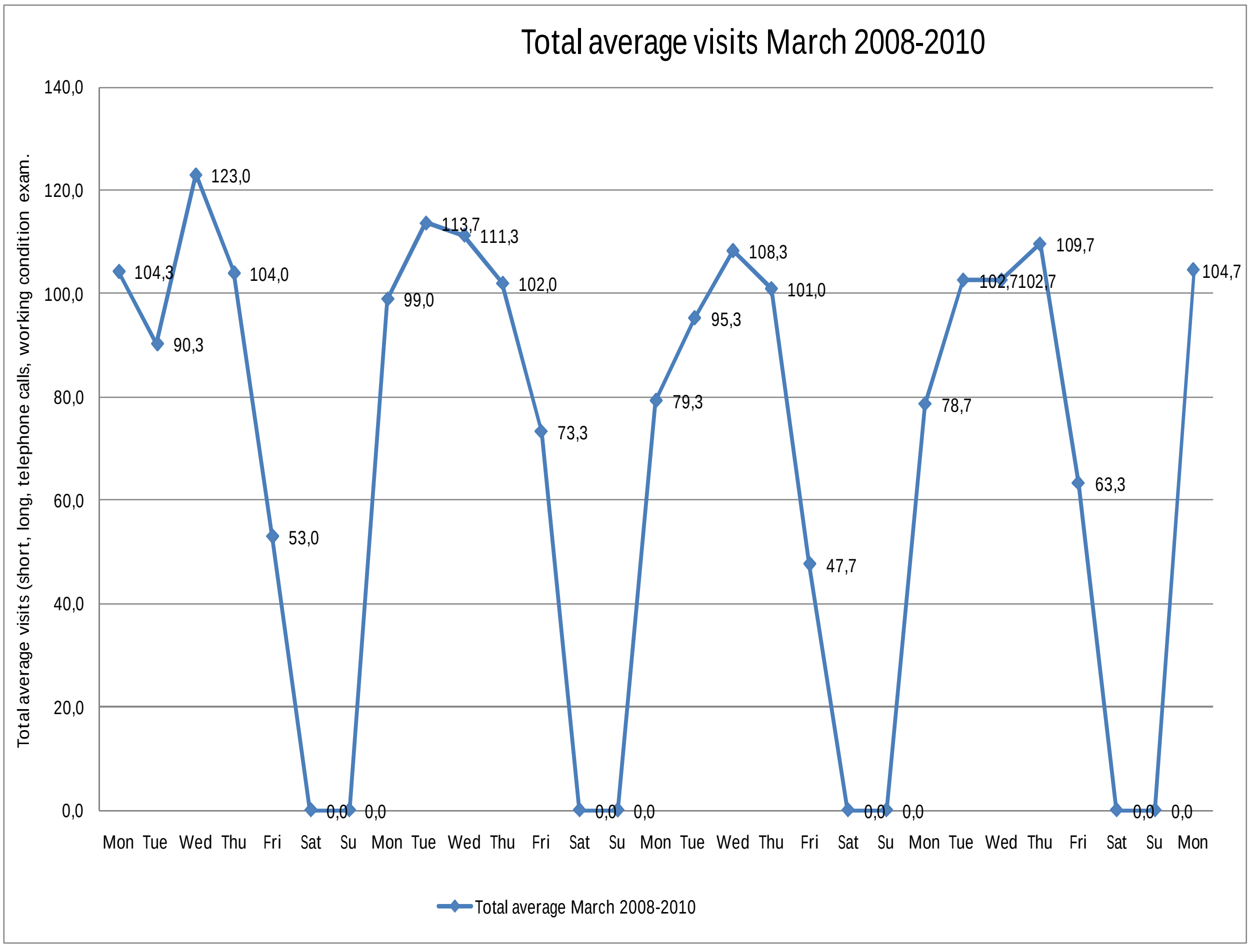


Figure 21. Total average visits March 2008-2010.

The Figure 21 shows the total average visits for the case organization business unit in March between years 2008-2010. Average data's are calculated from the total average numbers of the selected data groups. High peak periods can be observed in the beginning of the week. Also in the middle of the week on Wednesday there seems to be high average numbers.

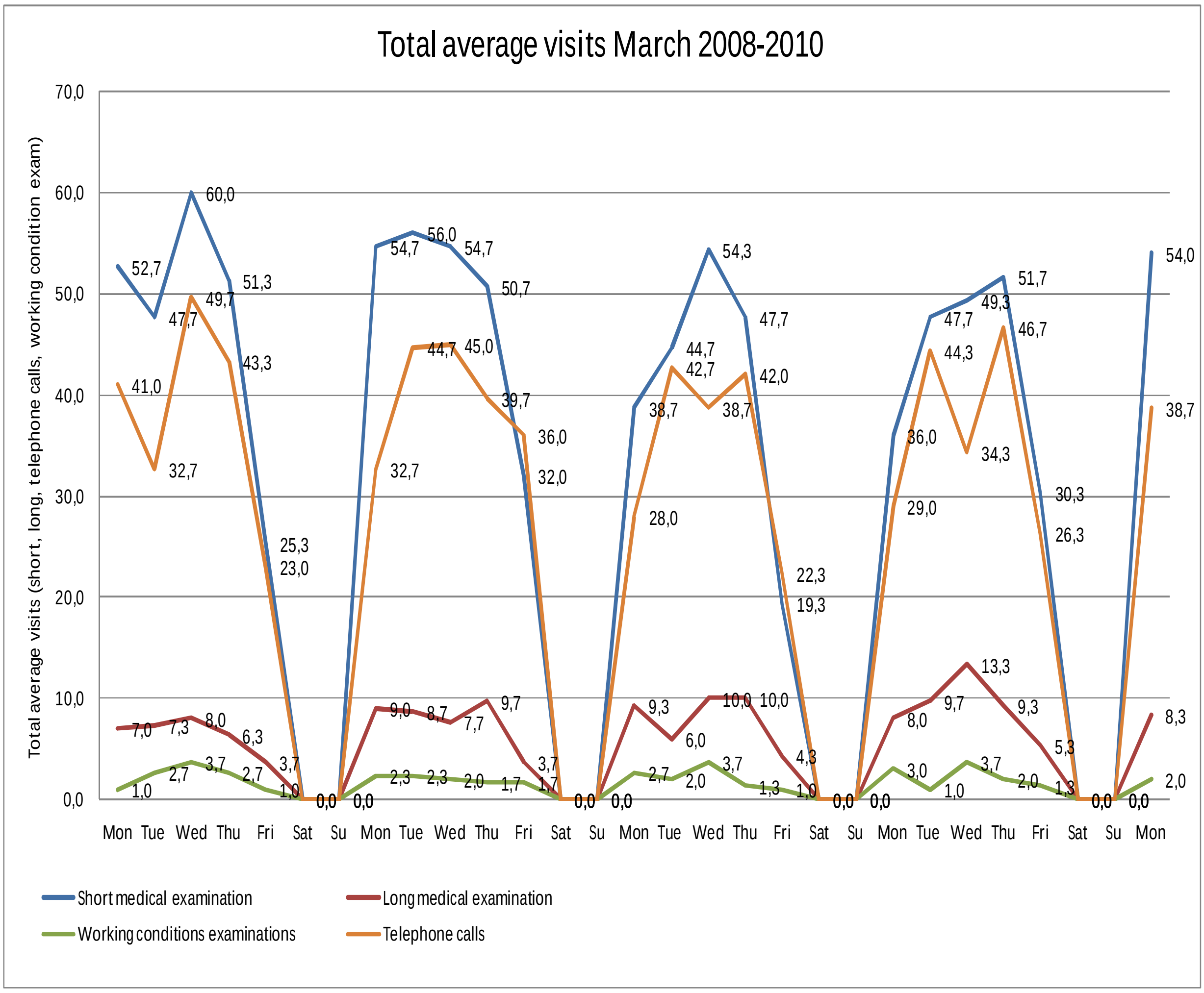


Figure 22.Total average visit groups March 2008-2010.

The Figure 22 illustrates the total average visit groups in March (average in 2008-2010). The figure shows the outsized need for the short medical examinations and it have the largest need in average. Short medical examinations peak times are consentrated on Thuesdays and Wednesdays. Long medical examinations do not have that eye-catching average during the week time. Telephone consultations are reaching the top avarages in the middle of the week. Eventhough these figures represents the facts of the provided services.

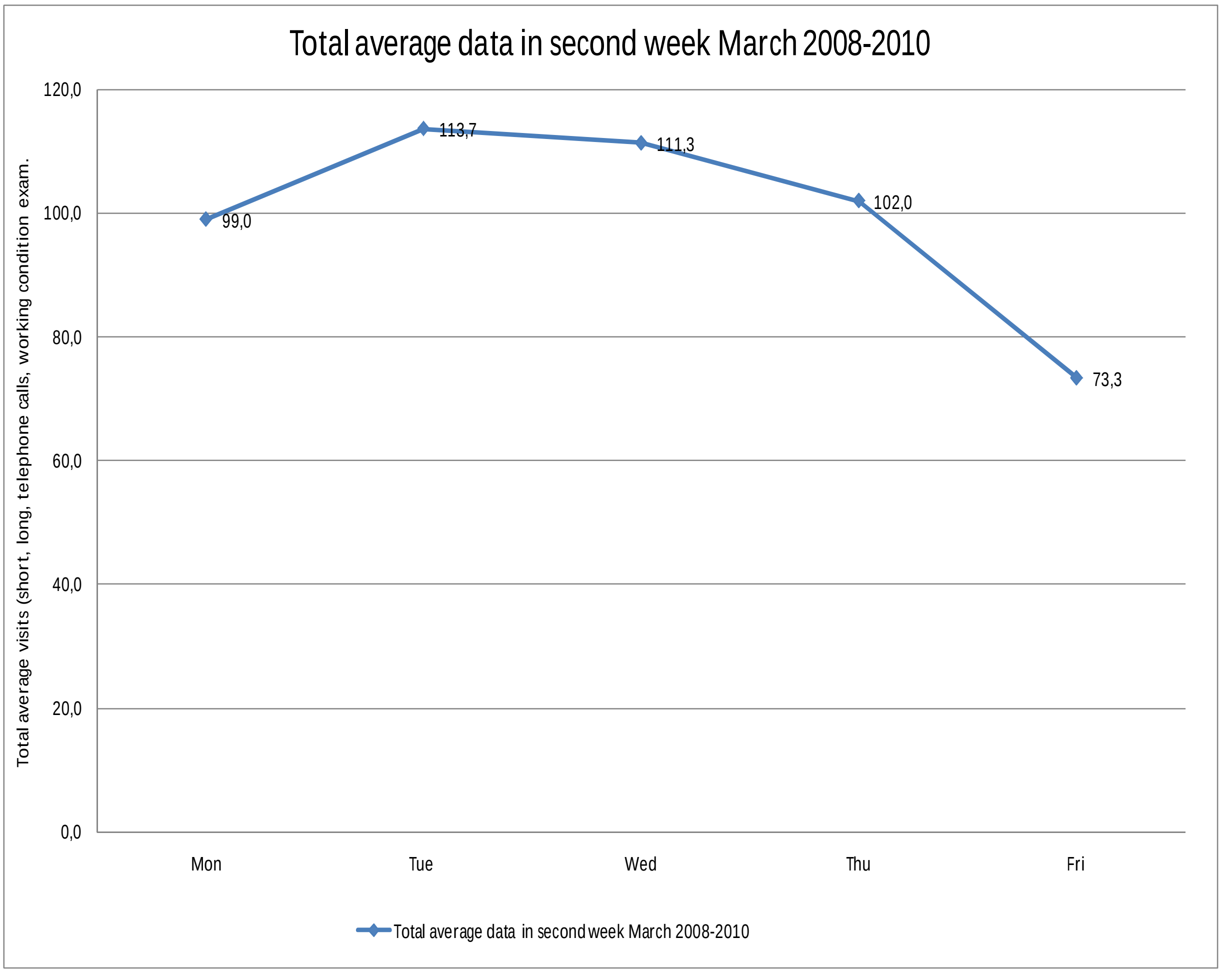


Figure 23. Total average data in second week (March 2008-2010).

The Figure 23 illustrates the total average visits in second week in the years 2008-2010 and in March. Figure illustrates the fact that patients are having more services in the beginning of the week. That might be the signal for that the services are also more available in the beginning of the week for example there might be lack of resources in the end of the week.

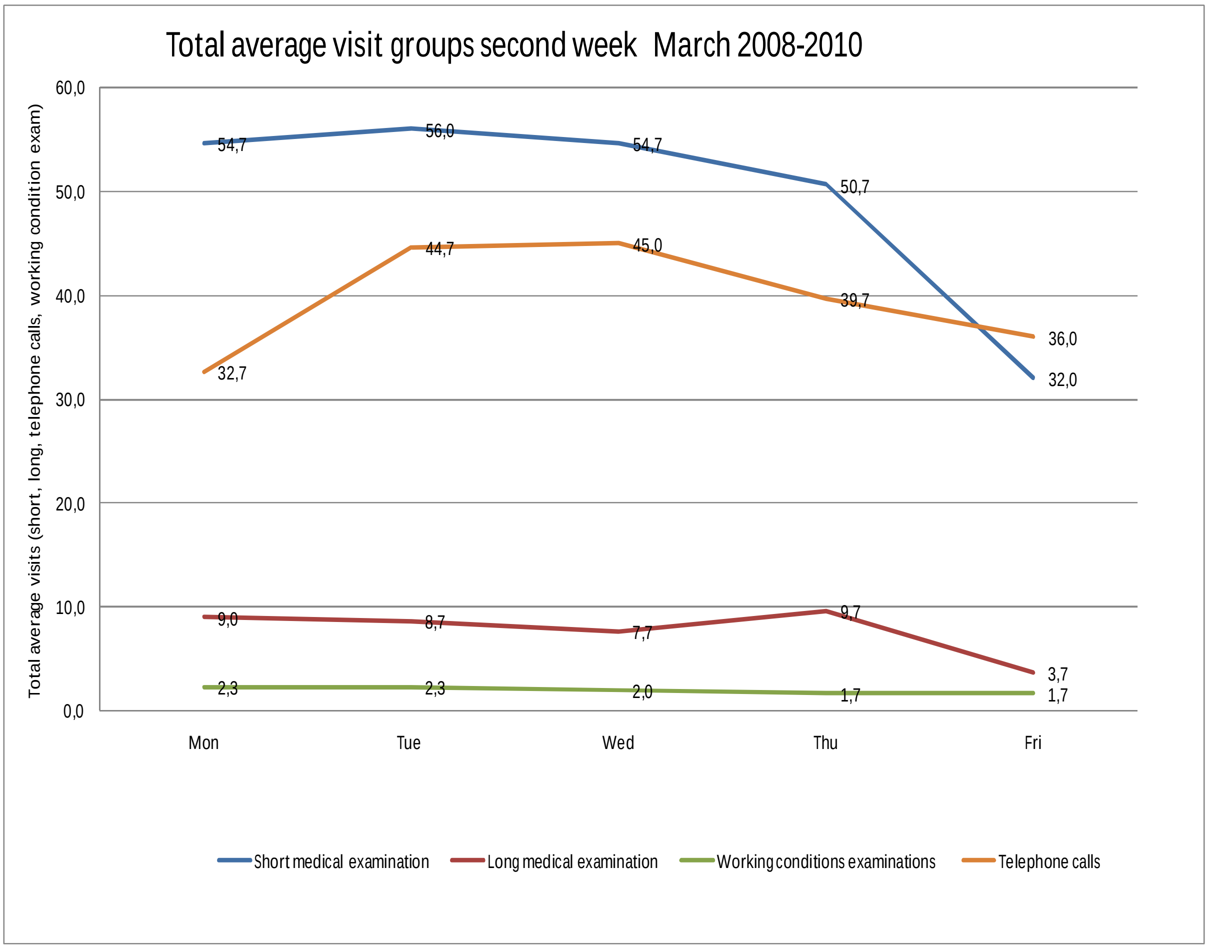


Figure 24. Total average visit groups second week March 2008-2010.

Figure 24 draws the total average numbers for the visit groups in March (Data for the years 2008-2010). Short medical examinations are done mostly in the beginning of the week. Long medical examinations are having stable volume in average which might be also signal for growing need for that service. Working conditions examinations do not have any peak periods during the selected average week. Telephone consultations are having peak periods in the beginning and in the middle of the week.

These figures are averages of the outcome of the total consultation of the provided services in the selected business unit. These above mentioned figures shows the fact, that time series forecasting can be used as a forecasting tool for analyzing the demand of the case unit doctors and their customers.

5 Analyses of the Forecasting Tools

This section exhibits and analyses three different forecasting tools for the case organization business unit forecasting. At this point, the tools are introduced and tested in this Thesis. Forecasting models themselves were introduced in Research Method and Material section.

5.1 Analysis of the ARMA-model

This sub-section suggests the actual figures for the demand forecasting model. Sub-section 5.1 analyses ARMA Microsoft Excel Add-in tool. The data groups are descript as individual data set.

In Table 7, the time series is defined and used throughout in this study and all of the analyzed forecasting tools.

Timeframe	Short	Long	Working conditions	Phone calls	Total
2008:1	894	98	44	880	1916
2008:2	994	132	29	904	2059
2008:3	747	89	30	708	1574
2008:4	942	106	51	873	1972
2008:5	860	108	39	849	1856
2008:6	684	102	14	728	1528
2008:7	501	43	5	451	1000
2008:8	823	121	24	716	1684
2008:9	1056	108	46	908	2118
2008:10	890	142	55	906	1993
2008:11	780	145	43	782	1750
2008:12	948	98	44	814	1904
2009:1	964	111	44	791	1910
2009:2	850	96	42	768	1759
2009:3	1149	174	71	920	2314
2009:4	1166	173	34	837	2212
2009:5	923	199	30	780	1933
2009:6	890	182	22	739	1835
2009:7	652	90	3	498	1250
2009:8	972	178	42	735	1935
2009:9	1124	279	45	858	2342
2009:10	1329	230	40	880	2539
2009:11	1171	217	25	809	2293
2009:12	881	166	22	695	1798
2010:1	785	114	13	593	1530
2010:2	951	151	27	574	1747
2010:3	1136	272	37	848	2354
2010:4	927	177	28	706	1873
2010:5	1039	238	49	802	2165
2010:6	893	131	23	800	1849
2010:7	575	87	8	504	1174
2010:8	827	149	24	654	1654
2010:9	927	170	49	820	1984
2010:10	1017	301	51	811	2206
2010:11	1060	363	49	944	2448
2010:12	882	245	44	691	1882

Table 7. Time series for demand forecasting.

Table 7 illustrates short and long medical examinations, working conditions examinations and received phone calls in the selected business unit. They are presented as time series for the years 2008-2010 and total figures in monthly level for each above described series.

ARMA model is tested by using short medical examinations in the model. In the model value of p=1 and q=1 while constant is set to zero.

timeseries: Short examinations				
Method: Nonlinear Least Squares (Levenberg-Marquardt)				
date: 02-27-11 time: 15:56				
Included observations: 35				
p = 1 - q = 1 - no constant - manual selection				
	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	1,002925377	0,0033845	296,3312823	0
MA(1)	-0,964802158	0,0404057	-23,87789192	0
R-squared	-0,002322		Mean dependent var	923,285714
Adjusted R-squared	-0,032695		S.D. dependent var	173,812199
S.E. of regression	176,630740		Akaike info criterion	12,866383
Sum squared resid	1029547,809698		Schwarz criterion	12,955260
Log likelihood	-223,161707		Durbin-Watson stat	1,269417
Inverted AR-roots	1			
Inverted MA-roots	0,96			

Table 8. Forecasting matrix in short medical examinations.

Table 8 shows the mathematical numbers of the ARMA-model in short medical examinations. Standard error of the estimation is calculated to be as 0,00338. R-squared illustrates how well a regression line approximates real data points; an r-squared of 1.0 (100%) indicates a perfect fit. Here, in Table 8, we can see that R-squared and adjusted R-squared numbers are not supporting the linearity of the projection.

Period	Actual	Fitted	Residual
2	894	753,27159	140,7284061
3	994	1108,1328	-114,1327561
4	747	664,30078	82,69921526
5	942	946,96732	-4,967324496
6	860	1043,3083	-183,3083094
7	684	1045,8572	-361,8572084
8	501	529,58623	-28,58622567
9	823	619,98764	203,0123629
10	1056	1029,2224	26,77756583
11	890	976,76853	-86,76853238
12	780	697,99626	82,00373966
13	948	855,65587	92,3441269
14	964	991,72625	-27,72625132
15	850	580,23692	269,7630829
16	1149	875,09326	273,9067437
17	1166	1148,1452	17,85482523
18	923	941,47375	-18,47374911
19	890	1148,4271	-258,4270982
20	652	583,23837	68,76163489
21	972	756,50209	215,4979067
22	1124	714,37528	409,6247197
23	1329	1095,681	233,3189835
24	1171	1239,319	-68,31895991
25	881	1045,4915	-164,4915363
26	785	779,99821	5,001791698
27	951	763,95629	187,043706
28	1136	1167,8631	-31,86305884
29	927	848,45337	78,54662806
30	1039	1112,2575	-73,2575111
31	893	1284,2914	-391,2913656
32	575	702,20084	-127,2008416
33	827	852,14293	-25,14293183
34	927	863,96978	63,03022103
35	1017	916,16342	100,8365844
36	1060	1143,8135	-83,81354629

Table 9. Fitted versus Actual figures in the short medical examinations time series.

Table 9 presents the actual and fitted figures in the short medical examination of the time series. This figure conducts estimation for the time series

Table 10 gives the forecast figures for the Microsoft Excel Add-in.

Period	IR	Forecast
1	1,000000	965,443668
2	0,038123	968,267954
3	0,038235	971,100503
4	0,038347	973,941338
5	0,038459	976,790483
6	0,038571	979,647964
7	0,038684	982,513803
8	0,038797	985,388026
9	0,038911	988,270657
10	0,039025	991,161722

Table 10. Forecasting short medical examinations in 10 month period.

When using the ARMA-forecasting method based on time series analyses, the model itself does not try to model the seasonal variation, which this Thesis describes in section 4.2, Analyzing the Demand for the Case Unit Based on Background data. Therefore models have to interpret the seasonal effect of the data. Even though we use Arma model in this form, we can only make 1-3 moths forecasts, because it does not show the summer demand period for June, July and August so we have to observe the seasonality of the data manually.

ARMA Model is based on the above mentioned historical data. ARMA model shows that if reliable forecasting is wanted, the produced seasonal changes have to be considered. As the researcher conclusion, if changing the p and q values we can produce better fitting forecasts, but changing the parameters p and q do not take into consideration the seasonality. Therefore ARMA model is not recommended to use in this case study.

5.2 Analysis of the SARIMA-model

When using SARIMA (Seasonal ARIMA) model with SPSS-statistics with same data that is introduced in the Table 7, improved forecasts can be performed. Forecasting parameters are shown in Figure 13. The Figure 25 concludes the model which is used in the forecast. SARIMA (1,0,1) is selected to run the forecast in the model and each of the selected datasets.

Model Description

			Model Type
Model ID	Short_examinations	Model_1	ARIMA(0,0,0)(1,0,1)
	Long_examinations	Model_2	ARIMA(0,0,0)(1,0,1)
	Working_conditions	Model_3	ARIMA(0,0,0)(1,0,1)
	Phone_calls	Model_4	ARIMA(0,0,0)(1,0,1)
	Total	Model_5	ARIMA(0,0,0)(1,0,1)

Figure 25. Model description for SPSS statistics 19 SARIMA.

Model description for the SARIMA-model gives the following output in Figure 26.

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	,194	,080	,098	,281	,098	,098	,116	,191	,274	,281	,281
R-squared	,194	,080	,098	,281	,098	,098	,116	,191	,274	,281	,281
RMSE	133,638	112,696	14,843	307,475	14,843	14,843	40,512	109,492	238,836	307,475	307,475
MAPE	29,450	25,626	10,866	70,613	10,866	10,866	11,895	14,266	54,597	70,613	70,613
MaxAPE	235,976	254,540	68,720	665,844	68,720	68,720	76,536	87,605	469,601	665,844	665,844
MAE	97,728	81,965	11,587	225,262	11,587	11,587	31,688	76,901	174,181	225,262	225,262
MaxAE	360,703	323,032	39,049	876,045	39,049	39,049	97,469	309,926	649,325	876,045	876,045
Normalized BIC	9,379	2,301	5,793	11,855	5,793	5,793	7,288	9,790	11,264	11,855	11,855

Figure 26. Model fit for SARIMA (1,0,1).

In Figure 26, the model fit table gives better numbers for R-squared figures. Even though in this model all series were used at the same time, but there seems to be no evidence for better results, if using forecasting model as individual forecasts or all series run at the same table at the same time. See Figure 27 the Model fit statistics table.

Model Statistics

Model	Number of Predictors	Model Fit statistics							Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Statistics	DF	Sig.	
Short_examinations-Model_1	2	,098	,098	170,197	14,266	123,100	84,352	422,605	38,672	16	,001	0
Long_examinations-Model_2	2	,191	,191	66,182	38,582	51,789	273,357	155,889	31,542	16	,011	0
Working_conditions-Model_3	2	,134	,134	14,843	70,613	11,587	665,844	39,049	18,018	16	,323	0
Phone_calls-Model_4	2	,281	,281	109,492	10,866	76,901	68,720	309,926	11,834	16	,755	0
Total-Model_5	2	,267	,267	307,475	12,924	225,262	87,605	876,045	34,454	16	,005	0

Figure 27. Model fit statistics for using SARIMA(1,0,1).

In the Figure 27 can make assumptions that model is given improved figures when comparing R-squared figures for the Microsoft Excel Add-in tool for the ARMA-model which is introduced in section 5.1 and Table 8.

Figure 28 shows the forecasting results for the SARIMA (1,0,1) model.

Forecast

Model		Jan 2011	Feb 2011	Mar 2011	Apr 2011	May 2011	Jun 2011	Jul 2011	Aug 2011	Sep 2011	Oct 2011	Nov 2011	Dec 2011
Short_examinations-Model_1	Forecast	889,62	922,44	973,82	974,07	933,07	862,20	712,44	895,68	995,35	1024,01	980,31	919,26
	UCL	1212,78	1245,60	1296,98	1297,23	1256,24	1185,37	1035,60	1218,85	1318,51	1347,17	1303,47	1242,43
	LCL	566,46	599,28	650,65	650,90	609,91	539,04	389,28	572,52	672,18	700,84	657,15	596,10
Long_examinations-Model_2	Forecast	116,41	145,74	167,23	139,10	160,34	127,98	131,27	149,12	131,30	206,13	238,90	204,52
	UCL	245,83	275,16	296,65	268,52	289,76	257,40	260,69	278,55	260,73	335,56	368,32	333,94
	LCL	-13,02	16,32	37,81	9,68	30,92	-1,44	1,84	19,70	1,88	76,71	109,47	75,10
Working_conditions-Model_3	Forecast	33,06	32,73	41,68	36,17	37,63	24,79	15,45	31,79	42,94	44,36	38,20	36,76
	UCL	60,92	60,59	69,53	64,03	65,48	52,65	43,31	59,65	70,80	72,21	66,06	64,62
	LCL	5,21	4,87	13,82	8,32	9,77	-3,07	-12,40	3,93	15,08	16,50	10,34	8,90
Phone_calls-Model_4	Forecast	574,85	578,01	727,84	673,52	813,00	807,92	570,77	651,29	805,81	782,99	945,66	754,15
	UCL	746,02	749,18	899,01	844,69	984,17	979,10	741,95	822,46	976,98	954,16	1116,84	925,32
	LCL	403,67	406,83	556,67	502,34	641,82	636,75	399,60	480,12	634,63	611,82	774,49	582,97
Total-Model_5	Forecast	1637,60	1774,34	2132,64	1854,16	2037,15	1856,39	1469,14	1750,56	1946,69	2081,43	2234,22	1910,68
	UCL	2220,99	2357,73	2716,03	2437,55	2620,54	2439,78	2052,53	2333,95	2530,08	2664,82	2817,61	2494,07
	LCL	1054,21	1190,95	1549,25	1270,77	1453,76	1273,00	885,75	1167,17	1363,30	1498,04	1650,83	1327,29

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

Figure 28. Forecasting results table for the SARIMA (1,0,1) model.

Figure 29 gives the forecasting results as in the graph illustration.

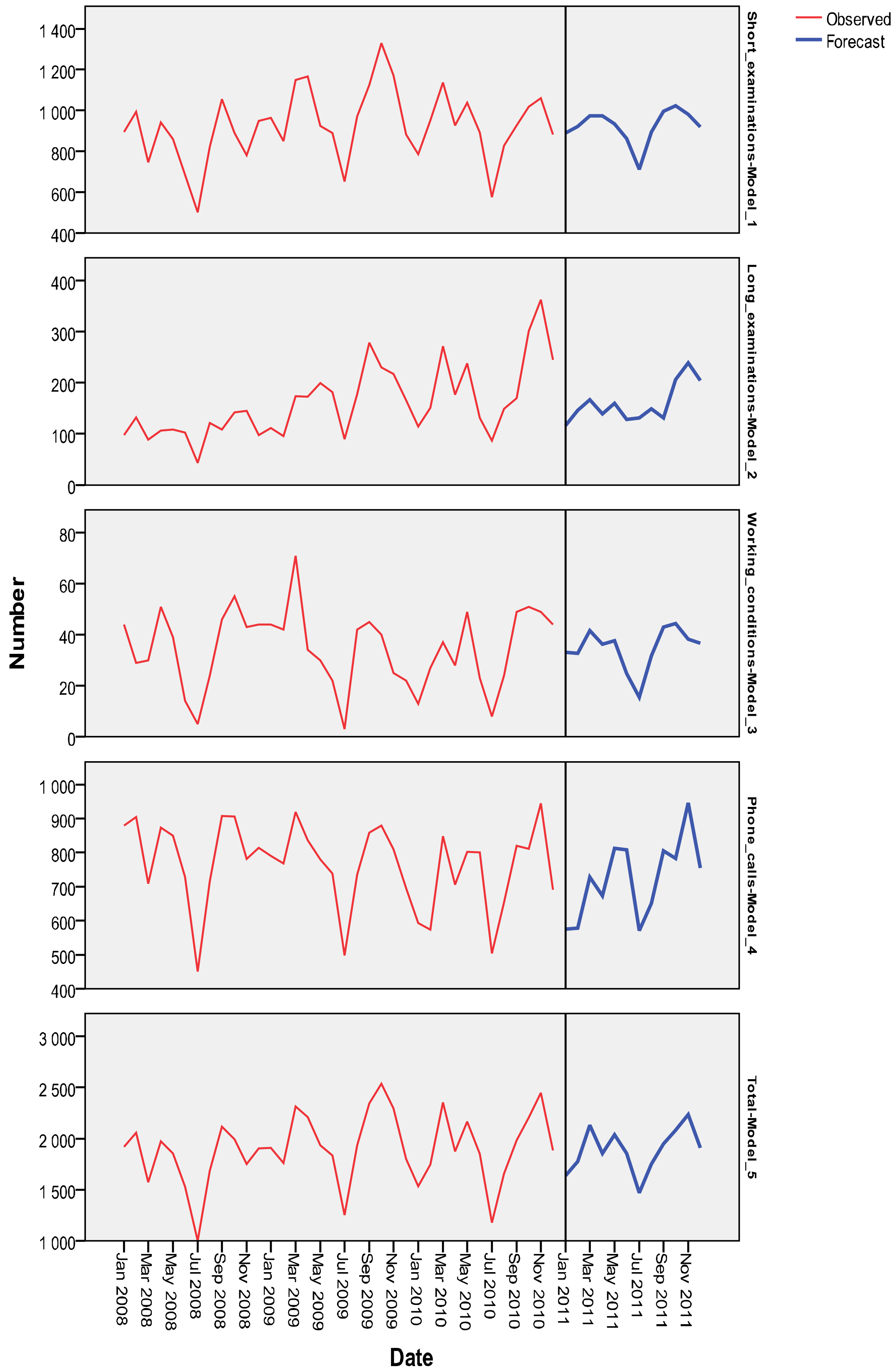


Figure 29.Forecasting results when using SARIMA(1,0,1) model for SPSS Statistics 19.0.

Figure 29 illustrates well the seasonality of the occupational healthcare services. Each individual series have seasonal effects in the background data and same phenomenon seems to be actualizing in the forecasting results, if looking at the short medical examination graph, long medical examination graph, working conditions graph and phone calls graph. Long medical examinations seem to have the smallest seasonality in the forecast. That might also express the fact, that long medical examinations are not that often provided and used or there might be constant need for the long medical examinations.

5.3 Analysis of the SARIMA Forecasting in Weekly Level

In this sub-section weekly forecasts are tested for using Seasonal ARIMA model. The data for a 3 year period were gathered in a day data format and fed in to the SPSS statistics 19.0 forecasting tool. Using SPSS-statistics and specifying used date variable as five working day variable for seasonal ARIMA (1,0,1) following figures can be observed. First if looking at the model fit figures following results are shown (see Figure 30).

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	,247	.	,247	,247	,247	,247	,247	,247	,247	,247	,247
R-squared	,247	.	,247	,247	,247	,247	,247	,247	,247	,247	,247
RMSE	12,657	.	12,657	12,657	12,657	12,657	12,657	12,657	12,657	12,657	12,657
MAPE	27,990	.	27,990	27,990	27,990	27,990	27,990	27,990	27,990	27,990	27,990
MaxAPE	687,475	.	687,475	687,475	687,475	687,475	687,475	687,475	687,475	687,475	687,475
MAE	9,878	.	9,878	9,878	9,878	9,878	9,878	9,878	9,878	9,878	9,878
MaxAE	62,369	.	62,369	62,369	62,369	62,369	62,369	62,369	62,369	62,369	62,369
Normalized BIC	5,112	.	5,112	5,112	5,112	5,112	5,112	5,112	5,112	5,112	5,112

Figure 30. Model fit (SARIMA (1,0,1) for short medical examinations day data in SPSS statistics 19.0.

Figure 30 R-squared numbers seems to be better than if comparing the figures between monthly data in the Figure 27 and day data in Figure 30.

Figure 31 illustrates beginning of the week effect that occupational services have on weekly demand. There might be more demand for doctor´s appointments on Mondays. Tuesdays and Wednesdays are having the highest demand when observing forecasting figures on week level.

Forecast

Model		152 1	152 2	152 3	152 4	152 5	153 1	153 2	153 3	153 4	153 5
Short_med_exam-Model_1	Forecast	34	46	46	49	35	34	46	47	50	38
	UCL	58	71	71	74	60	61	73	74	78	65
	LCL	9	21	21	25	10	7	19	19	23	10

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

Figure 31. Forecasting results for SARIMA (1,0,1) day forecast.

Figure 32 illustrates the overall short medical examinations at a day level. The length of the forecast is two weeks. The forecasted data do not include weekends; even thought occupational healthcare center is not providing service during the weekends, which is the reason why forecast and historical data is based on five days data sets.

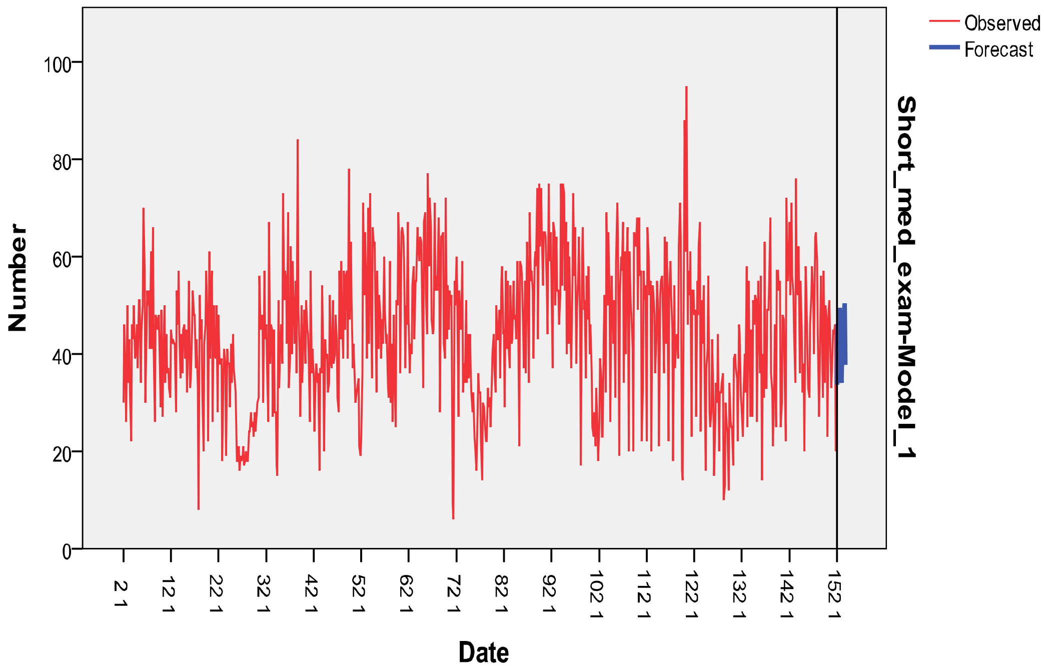


Figure 32. Forecasting day data SARIMA (1,0,1).

5.4 Analysis of the Expert Time Series Modeler

In the previous sub-sections analysis, SPSS Statistics 19 has shown improvement in higher R-squared numbers in Figure 26 and Figure 30. SARIMA-modeler, which takes into consideration the data seasonality, SPSS-modeler improves the forecasting accuracy one step ahead. Model description can be seen in Figure 33.

Model Description

			Model Type
Model ID	Short_examinations	Model_1	Simple Seasonal
	Long_examinations	Model_2	Winters' Additive
	Working_conditions	Model_3	Simple Seasonal
	Phone_calls	Model_4	Simple Seasonal
	Total	Model_5	Simple Seasonal

Figure 33. Model description for SPSS Statistics Expert time series modeler.

Model description for the SPSS expert modeler gives following output for how the model is functioning in Figure 34.

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile 5	10	25	50	75	90	95
Stationary R-squared	,737	,055	,666	,790	,666	,666	,678	,765	,782	,790	,790
R-squared	,646	,048	,591	,696	,591	,591	,596	,660	,690	,696	,696
RMSE	85,989	72,190	9,779	196,051	9,779	9,779	24,855	73,007	153,614	196,051	196,051
MAPE	15,106	9,301	7,415	27,897	7,415	7,415	7,913	9,692	25,005	27,897	27,897
MaxAPE	54,917	39,676	28,835	122,245	28,835	28,835	30,022	32,591	90,974	122,245	122,245
MAE	68,171	58,157	7,707	157,351	7,707	7,707	20,168	53,786	123,366	157,351	157,351
MaxAE	202,458	182,062	19,593	491,245	19,593	19,593	54,063	169,459	367,352	491,245	491,245
Normalized BIC	8,318	2,288	4,760	10,756	4,760	4,760	6,216	8,780	10,189	10,756	10,756

Figure 34. Model fit for SPSS Statistics 19.0 Expert modeler.

SPSS statistics Expert modeler increases the R-squared figures if comparing the numbers between the Figure 26 and 30 in previous sections monthly and day data forecasts in the SARIMA model.

Model Statistics

Model	Number of Predictors	Model Fit statistics								Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	RMSE	MAPE	MAE	MaxAPE	MaxAE	Normalized BIC	Statistics	DF	Sig.	
Short_examinations-Model_1	0	,790	,591	111,178	9,692	89,380	32,591	243,458	9,621	30,949	16	,014	0
Long_examinations-Model_2	0	,666	,696	39,931	22,113	32,628	59,703	88,534	7,673	23,702	15	,070	0
Working_conditions-Model_3	0	,765	,601	9,779	27,897	7,707	122,245	19,593	4,760	24,600	16	,077	0
Phone_calls-Model_4	0	,691	,660	73,007	7,415	53,786	28,835	169,459	8,780	12,772	16	,689	0
Total-Model_5	0	,775	,683	196,051	8,411	157,351	31,210	491,245	10,756	24,425	16	,081	0

Figure 35. Model fit statistics for SPSS expert modeler.

Figure 35 SPSS statistics expert modeler increases the R-squared number at its highest when comparing results between ARMA model in Table 8 and SPSS Statistics SARIMA model in Figure 26. Therefore when comparing the results between above mentioned R-squared numbers SPSS Statistics Expert modeler seems to be construction increased R-squared numbers with the background data.

Forecast

Model		Jan 2011	Feb 2011	Mar 2011	Apr 2011	May 2011	Jun 2011	Jul 2011	Aug 2011	Sep 2011	Oct 2011	Nov 2011	Dec 2011
Short_examinations-Model_1	Forecast	875,51	926,17	1005,17	1006,17	935,17	816,84	570,51	868,50	1030,17	1073,17	998,17	898,17
	UCL	1101,45	1156,59	1239,98	1245,29	1178,52	1064,35	822,11	1124,13	1289,77	1336,67	1265,52	1169,31
	LCL	649,57	695,76	770,37	767,06	691,82	569,33	318,90	612,87	770,58	809,67	730,82	627,03
Long_examinations-Model_2	Forecast	201,34	220,00	272,00	245,67	275,34	232,00	167,00	243,00	279,34	318,00	335,34	263,34
	UCL	282,58	301,64	354,04	328,10	358,16	315,22	250,61	327,00	363,72	402,77	420,49	348,87
	LCL	120,10	138,36	189,97	163,24	192,51	148,78	83,39	159,01	194,95	233,23	250,19	177,80
Working_conditions-Model_3	Forecast	39,31	38,31	51,65	43,31	44,98	25,31	10,98	35,65	52,31	54,31	44,65	42,31
	UCL	59,19	59,72	74,48	67,49	70,43	51,98	38,80	64,58	82,32	85,36	76,69	75,33
	LCL	19,44	16,91	28,81	19,14	19,53	-1,35	-16,84	6,71	22,31	23,27	12,60	9,30
Phone_calls-Model_4	Forecast	739,48	733,48	810,15	790,15	795,15	740,48	469,15	686,48	846,82	850,48	829,82	718,15
	UCL	887,85	882,59	959,99	940,73	946,46	892,52	621,91	839,96	1001,01	1005,39	985,43	874,47
	LCL	591,11	584,37	660,30	639,57	643,84	588,45	316,39	533,01	692,63	695,58	674,21	561,83
Total-Model_5	Forecast	1770,12	1839,79	2065,45	2003,79	1969,45	1722,12	1126,12	1742,45	2132,79	2230,79	2148,45	1846,12
	UCL	2168,54	2238,21	2463,88	2402,21	2367,88	2120,54	1524,54	2140,88	2531,21	2629,21	2546,88	2244,55
	LCL	1371,70	1441,36	1667,03	1605,36	1571,03	1323,70	727,70	1344,03	1734,36	1832,36	1750,03	1447,70

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

Figure 36. Forecasting result table SPSS Statistics 19.0 Expert modeler.

Figure 36 gives the forecasting results with SPSS Statistics 19.0 Expert modeler. Forecasting results seems to be in line with the background data analyses in section 4.2 and in Figure 17 Total average of the selected doctor’s events realization. Figure 37 represents similar results if comparing the illustrations between the Figure 17 and Figure 37 total outcomes.

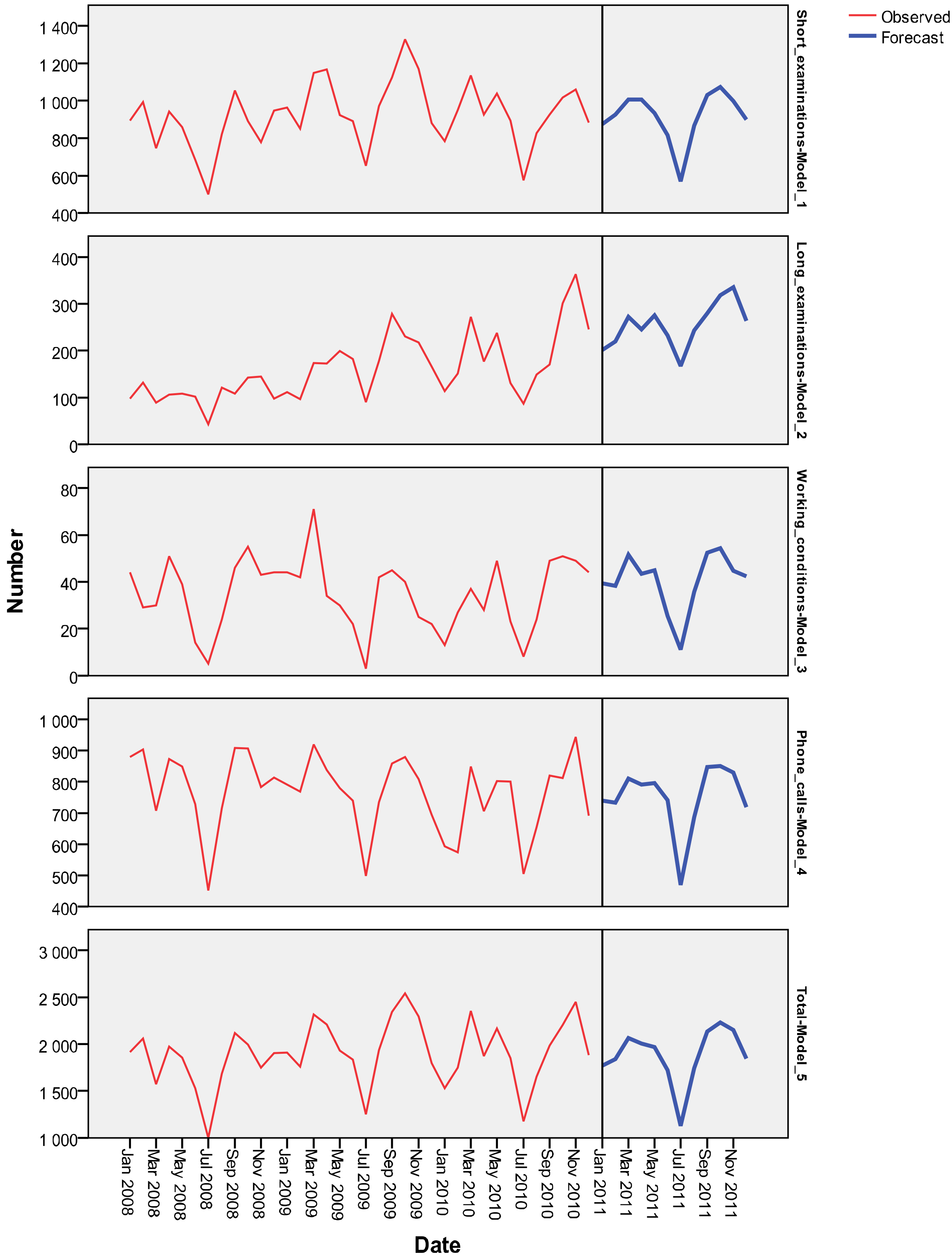


Figure 37. Forecasting results in illustration when using SPSS expert modeler.

When comparing the results between Figure 29 and Figure 37 both illustrations show the seasonality change of the forecasting in occupational healthcare services. Each individual series has seasonal effects in the background data and same phenomenon seems to be occurring in the forecasting results. When comparing Figure 37 to Figure 29 it looks like that also long medical examinations have the seasonality change in the forecast. Historical background data analyses which are made in section 4.2 have shown the seasonality change of the background data which overrules the SARIMA model conclusion in section 4.2 and in Figure 29, which long medical examinations do not have the same seasonality change which other service groups seems to have.

5.5 Validating the selected model

This sub-section validates the selected model. The ARMA-model as a Microsoft Excel Add-in was introduced in the section 5.1 is analyzed based on the tests run in the same section. ARMA-model itself does not observe and take into consideration the seasonality change, which has been shown in the section 4.2. R-squared figures were also quite low in ARMA-model. SPSS statistics offers the SARIMA model (Seasonal ARIMA) which is concerning the seasonality of the background data. Figure 27 shows increased values for R-squared figures, when comparing results between ARMA model results in Table 7. Taking one step ahead for SARIMA model and using the SPSS statistics Expert modeler can gain more accurate investigation results. Figure 35 increases R-squared numbers up to even 0,79 for the short medical examination. Figure 35 R-squared number is closer to 1,0 and that confirms that forecast results are more valid if comparing to ARMA and SARIMA R-squared numbers.

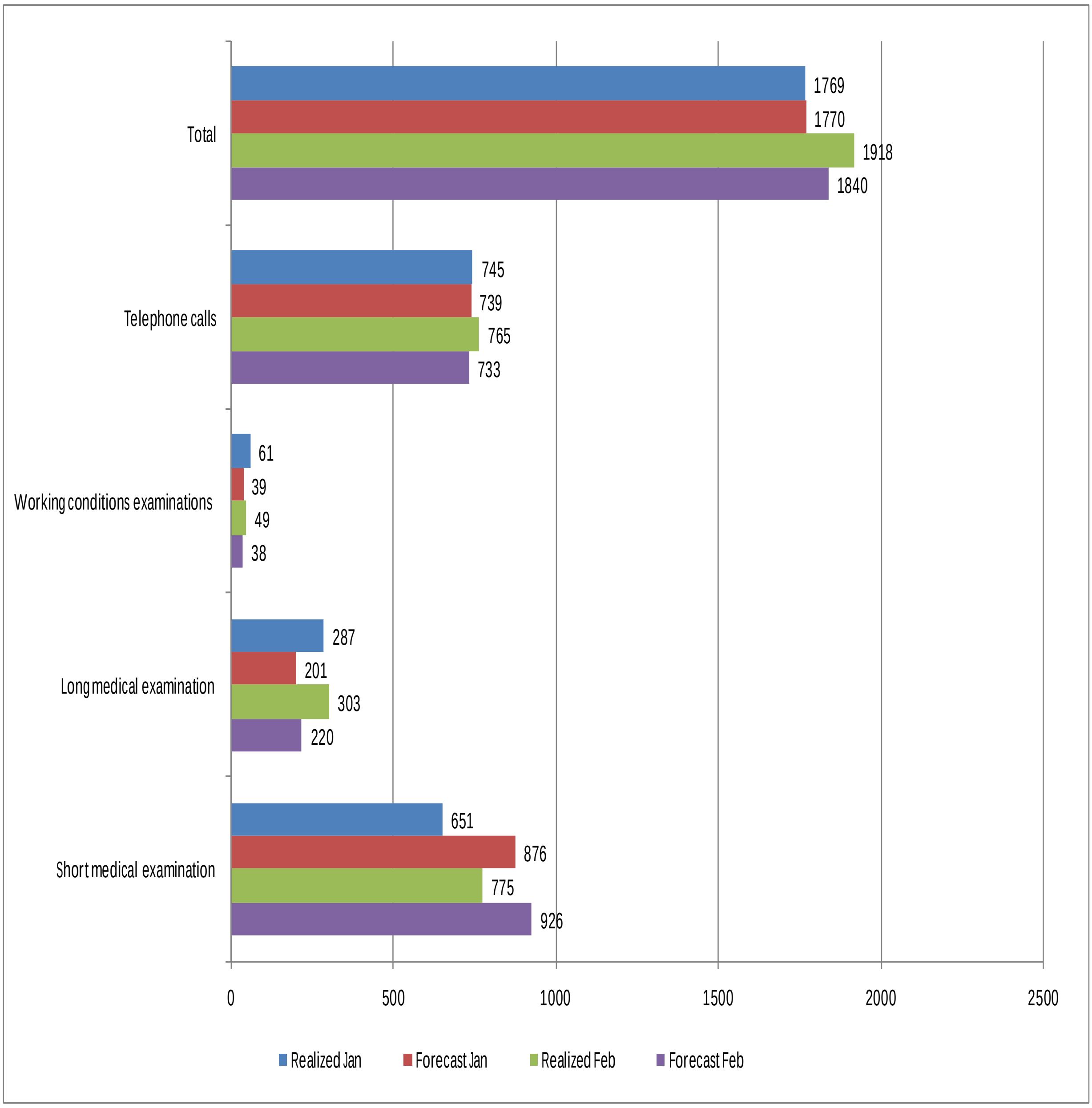


Figure 38. Comparing the Forecast and Realized numbers during the January and February 2011.

Figure 38 Comparing the Forecast and Realized numbers between different units of care groups during the January and February 2011 gives a good comparison overview for the SPSS Statistics 19.0 expert modeler. Figure 38 shows that forecasting results can fit in the data when comparing the results between the forecasting results produced with SPSS Statistics Expert modeler and for the actual units of care realization in the beginning of the year 2011. Trend seems to be similar when looking at the results in the Figure 38 and comparing them to results shown in the background analyses section 4.2 and forecasting results in the Figure 37.

Figure 39 concludes that January has minor service consumption the selected service groups if comparing results and forecast to February.

Year 2011	Realized Jan	Forecast Jan	Realized Feb	Forecast Feb	Difference Jan	Difference Feb
Short medical examination	651	876	775	926	225	151
Long medical examination	287	201	303	220	-86	-83
Working conditions examinations	61	39	49	38	-22	-11
Telephone calls	745	739	765	733	-6	-32
Total	1769	1770	1918	1840	1	-78

Figure 39. Forecasting and actual event realization comparison in numbers.

Based on this statistical observations and results of the SPSS Expert time series model it is recommended to use it in the Occupational healthcare service forecasts.

5.6 Management interview analyses

Line management and top management were interviewed after presenting the background data analyses in section 4.2 and after analyzing forecasting tools in section 5. Interview template can be found on the Appendices (Appendix 1). Interview questions were straighten the following issues:
How managers were seen the business unit healthcare service demand?
How service provision will effect to the service demand?
How managers see the service provision change in the past three years
How they can explain the non-seasonal changes of the service provision
Also open discussions for the forecasting results were done during the interviews. In addition, the objective was that the interviews confirms the fact that represented forecasting tool could used in the case business unit and from the time being in the whole organization

Management interviews were conducted for the selected business unit management team which consist two managers. Also the CEO of the OHCC was interviewed. When analyzing the forecasting results with line and top management the following conclusions can be made.

The managing doctor of the selected business unit highlighted the fact, that in historical data analyses, non seasonal changes can explain the possible short temporary post assignments for the doctor's positions. Also holiday seasons in spring and autumn time reflects to the provided service. The managing doctor and the managing nurse of the selected business unit concluded that changing the process for phone call services in 2009 has stabilized the provided service volumes when looking at the background data analyses in section 4.2 and the SPSS statistics expert modeler forecasts in Figure 38. Managing doctor also pointed out the fact that changing the weekly meeting time processes might have an influence for the provided services. Friday afternoon service hours are reserved for the writing work and team meetings which reflect the low figures on Fridays.
When analyzing the forecasting results and realized events on January and February following conclusions can be done with the management interviews. January is partly holiday season and that is effecting directly for the January results. This was confirmed with the whole management team.

Forecasting could help improve the business unit holiday planning if holidays are held more on low seasons.

When looking at the forecasting results and looking the actual forecast in the interviews, is noticed that the actual forecasting environment is larger and better results can be gained for forecasting. This means that selected SPSS expert modeler could also be functioning in the whole organization. Managing doctor of the selected business unit suggests that; one way to handle the demand better is to differentiate occupational services. It can be differentiated to working conditions examinations, long medical services and the short medical examinations which can be often specified as bulk service, for example diagnosing some minor diseases flu and influenza. These kinds of bulk services might be more easily to outsource or rent more doctors in-house to provide the bulk service. Then in-house personnel could concentrate more on the long medical examinations and working conditions examinations.

Management team confirms that this kind of bulk service changes have already been launched to respond better for the demand need. In short term, medical services are constructed in a way, that part of the doctors are specialized for providing the bulk services and some doctors are only providing long medical services and working conditions services. These kinds of changes in the service process might gain better abilities to respond the demand.

Management team pointed out the fact that; The service agreements between the outsourcing services or firms that are renting the doctors in-house firms can be redefined in a way, that these service providers must commit to provide short term medical services, in a short notice to better respond for the changing demand in short period of time. Line management interviews pointed out the fact that forecasting result can be provided for the outsourcing partner to plan their resources better and to better respond on changing demand. With better cooperation improved service chain can be gained.

6 Discussion and Conclusions

This Thesis has investigated and analyzed the demand that Helsinki City Occupational Healthcare Center and its selected business unit doctors are facing on annual, monthly and daily level. Main purpose for this Thesis is to help the OHCC top and line management to plan the workload in different times and situations. This study provides information for healthcare organizations to better explain how to improve their performance through forecasting. The availability of additional forecasting information helps the line managers involved in a specific medical process, to make prompt decisions and align different units that manage each separate part of the healthcare process. Improved forecasting, without related process or layout modification, provides only limited performance improvement.

This Thesis first introduced the findings from the literature, how healthcare organization should select the forecasting model and built the forecasting process. Current status analyze of the case business unit customers is introducing demographic information such as age profile of the selected customers. Historical background data analysis has pointed out the fact, that OHCC has seasonal changes in the service provision. In the section 5 three different forecasting models are introduced and tested. Comparison is done with R-squared method which is introduced in this Thesis. Selected and proposed model is tested and compared with the actual service group event realization figures from the January and the February 2011. Management interviews were conducted after analysis and selection of the forecasting model. Management interviews consists the two managers of the selected business unit and the CEO of the OHCC. Discussion and conclusion part polishes the selected model.

Suggested forecasting model has been limited for the research reasons in one selected business unit and its doctors and their customersThe outcome of this Thesis represents a tool and model for predicting demand on a monthly level. This study is not only providing a model for sales forecasting. This Thesis is more complex than normal sales forecasting process, because of the complexity of the whole healthcare process, which is presented in the Figure 2 at the literature analysis section. Need, demand and supply of the healthcare services are tight in the healthcare service provision.

The literature review has showed different options in service business and in the healthcare services for forecasting and demand analyses. Customer demand analyzes can be measured in different ways. The literature review shows the models how organization should investigate and try to understand the population and their healthcare needs better. Organization managers have to select the right items for forecasting. Healthcare service which are investigated are implemented as doctor's short medical examinations, long medical examinations, working conditions examinations and examinations services provided through phone calls. These cares of unit groups has been selected for the main forecasting unit because they are available in the right format for forecasting. Because this Thesis case business unit has not been having large changes in customer population or in the organization itself this is the reason why additional data interpretation is not needed. For further analyses in different organizations and different business units it is important for forecasters to understand the historical changes in the forecasted environment. To implement the forecasting process in use for the selected organization is the starting point in creating customer demand analysis. In the forecasting process, if organization has empty spots in the forecasting process, that can cause data misinterpretation and forecasting errors. Literature points out the fact that historical background data analyzes are important for the organization which is starting to develop forecasting process. Historical data can indicate the possible seasonality and trend effects of the healthcare services.

The purpose of this thesis is to build up the ground for forecasting methods and give the opportunity for the organization to use them. One of the main goals for the literature review is to understand the customer and its population more clearly and to clarify the other critical aspects when starting to analyze the historical data and constructing the forecasting methods. This Thesis is examining the Human resource data such as age and other demographic data of the case customer population in order to create a better understanding of the customer demand base. Human resource data is not added to the forecasting tool which is introduced in the section 4. Human resource data in this Thesis gives more background information for how to analyze the customer demand forecasting in the selected business unit.

Stark et. al. (2008) proposes in literature review that organization should answer the five key questions to establish the business need and to clarify demand forecast.

This Thesis answers these five key questions as follows. Forecasting in this study will influence the workload planning and gives better understanding of the demand which selected business unit doctors confronts. Key stakeholders of this study are the line managers of the selected business unit and the top management of the OHCC. Metrics which are used in the forecast are defined to be the selected groups of the units of care and the actual events of the OHCC patient care system are status “Ready”-events. These status “Ready”-events consist the needed timestamp which can be exploited in the forecasting. It is important to understand the trends and seasonality issues in the forecasted data. This Thesis introduces model which is looking the forecast projection 2-4 months ahead. Model provides an opportunity to make forecasts in more detailed level, but this Thesis recommends that the actual forecasts should be made at 2-4 months period. Accuracy of the forecasts will be measured by using forecasting error tools such as introduced in section 3.3 forecasting errors. Statistical software’s such as SPSS statistics have built-in these features. In this Thesis the forecasting accuracy is measured with using R-squared method. R-squared method is used in this study to illustrate how well the regression line approximates real data points. This Thesis recommends that any forecasting which is done for any organization should be aware of the forecasting errors and it is recommended to use at least two different models to approve the forecasts as precisely as possible. Even though, anybody cannot predict the future precisely.

In this study the literature analyses show that different forecasting approaches can be suggested and they can be used in the different customer categories. Literature review points out that forecasting method can be categorized as judgemental or statistical methods. This Thesis is using statistical method for the forecasting. Two different forecasting models and two modification of the other are introduced in this Thesis. Models which are introduced are Arma model, ARIMA model, Seasonal ARIMA and SPSS expert Modeler which take into consideration seasonality and compare the results by mixing ARIMA and exponential smoothing models. SPSS expert Modeler has also been selected as the main tool for the case organization business unit.

Time series models such as ARMA, ARIMA and SARIMA models are introduced in Research Method and Material section. This study introduces the forecasting errors. Often forecast accuracy is measured, but it is not identified what are the impacts of forecast errors. Forecasting accuracy is measured in this Thesis by looking at the R-squared measures which are used quite often in literature to measure the forecasting accuracy.

ARIMA modeling can take into account trends, seasonality, cycles, errors and non-stationary aspects of a data set when making forecasts and for that reason ARIMA model and its variations are selected in this Thesis to conduct the Healthcare service demand forecasting.

Section 4 analyses the selected business unit customers. Age as a variable should be considered when validating the forecasting results. In this study researchers main purpose was to keep the forecasting variables as simple as possible in order to build up as clear model as possible. Literature review has also pointed out that, the more complicated the model is more difficult it is to produce reliable forecasts. Even thought the age seems to be the constant factor when prospect customers are facing the need for occupational healthcare services. When analyzing the HR results in the section 4 following conclusions can be done. Age is factor that has to be considered when any healthcare service is provided if the information of the customer population is available.
As shown in the Table 6 (Age differentiation table) following assumptions can be made. Now the largest population group is 50-59 years old and that might cause an extra need for healthcare services after few years, even though OHCC has already started projects for preventative healthcare services, which might change the demand peeks after few years. The results of these projects have to be considered when conducting forecasting methods after few years.

The knowledge of the current customer population is important for the healthcare service provider. In that sense, occupational healthcare provider can make deeper analyses of its customer population, because it usually has a wider knowledge of its customers, when comparing for example to public hospital, which has more limited information about its customer base.

A historical data analysis of the selected case customer population gives a good overview of the services used in the previous years. That also helps the line management and top management to adjust the decisions concerning the workload between individual teams and between different business units. Historical data also points outs clearly the seasonal variations of the occupational healthcare services provided to the customer.

When analyzing the forecast results in the section 5 the customer demographic information has to take into consideration in the analysis.

When using ARMA model to forecast case customer demand following conclusions can be made. ARMA model do not take into the considerations the seasonality of the background data which Occupational healthcare services seems to have when looking at the historical data figures in section 4. ARMA model uses on p and d values which do not calculate the data seasonality change of the background data if there one exists. ARMA model can be used in case organization if the forecasting is limited to one or two week timeframe. After longer period ARMA model gives only figures that represents growing time series which do not fit in the case organization or in the Helsinki City OHCC historical patient background data or the actual results which are seen in the beginning of the year 2011. Also different numbers were tested how they could fit in the ARMA model, even though the results seems to have the same paradigm that ARMA model cannot acquire the forecasting accuracy with the OHCC demand forecasting.

Seasonal ARIMA fits better to case business unit customers demand forecasting. Seasonal ARIMA uses the SARIMA (1,0,1) model which also observes the seasonality of the historical background data. Results that are represented in the section 5.2 Adding variables to the SPSS-statistics SARIMA-model. Figure 26 gives improved results for the R-squared figures, if we compare them to same figures for the ARMA model in Table 8. This also confirms the fact that ARMA model is not working in the case healthcare data and as forecasting method for the case organization business unit. Forecasting results in the Figure 28 and 29 shows relatively good forecasting results and seems to be that

SARIMA model is forecasting high seasons in spring time to February, March and April and for the another high season in September and November.

When using SPSS statistics 19 and SARIMA (1,0,1) model for the day level forecasting we can see in the Figure 30 for short medical examinations day data in SPSS statistics that R-squared figures are boomed if we compare results for the SARIMA monthly level forecasting to 0,096 for day level results 0,247. Even when the above mentioned results were good in research point of view the purpose was to find the best fitting model for demand forecasting.

This Thesis also introduces and analyses the SPSS statistics Expert modeler method which uses both ARIMA model and Exponential Smoothing methods, and combines the seasonality change of the historical background data. In section 5.4, Adding data to SPSS Expert time series modeler, we can be seen the improved outcome if starting to compare the R-squared figures in the Figure 34 Model fit statistics for SPSS expert modeler. R-squared figures are increased if looking at the short medical examinations from SARIMA model 0,247 to expert model 0,79 which shows large growth in numbers. In Figures 36 and 37 we can see that also long medical examinations have the seasonal effect which the background data analyzes have been pointing out in the Section 4 Current status analyzes of the Case organizations customers graphs. That also overrules the SARIMA model conclusion that long medical examinations do not have the same seasonality which other service groups seems to have. When constructing forecasts with SPSS statistics expert model the figures also replicates existing conditions which is a good point of reference when evaluating forecasting tools. When comparing forecasting results constructed with SPSS expert modeler and actual event realization in Figure 35 and 36 we can see that SPSS expert modeler is giving good results, if comparing results between ARMA and SARIMA model. Also the trend between January and February seems to be similar when looking at the results in the Figure 38 and Figure 39.

When analyzing the forecasting results with line management following conclusions can be made. Forecasting results can help the outsourcing partners to respond the changing demand better. Forecasting tool will help line managers to plan better the workflow between different annual periods. Forecasting model results are suggested to draw the big picture for the customer demand for the line managers and also for the top management to better analyze the customer demand.

The above mentioned results for the SPSS statistics expert modeler concludes that the expert modeler fits best for these introduced models as a forecasting tool for the OHCC selected business unit and predicting its doctor demand. It can also be recommended that forecasting should be done on a monthly level. Even though weekly and even daily level forecasts are possible, but might not offer any extra benefit to the line management or top management.

6.1 Proposed Tool for the Case Organization

This sub-section identifies and builds together a model based on the above mentioned datasets and analyses of the case organization selected business unit. Model is integrated to operational and financial planning and is working in one selected system first on Microsoft excel spreadsheet and compared forecasting is done by using SPSS statistics SARIMA model and Expert modeler. Main goal for the tool is to give a simplified tool and the ability to frequently reforecast and to respond to business changes with “what if” scenarios as often as necessary.

Forecasting model is tested and verified with the line management. Demand forecast will be updated each month with last month results of the case organizations business unit.

Forecasting results are presented as a Dashboard. The Dashboard gathers up the results that are used in the forecasting. Dashboard includes the last month’s results and also three years of historical data to illustrate the seasonal effects that OHCC is meeting annually. Section five shows that SPSS statistics expert modeler can provide functional tool for forecasting. Forecasting figures are added to the forecasting model after each month and forecast is done based on the historical background data. SPSS-statistics expert time series model concerns the seasonality of the occupational data and therefore the line management can observe and make decisions based on the forecasts.

6.2 Managerial implications

Managerial implications in this Thesis are the tool for healthcare managers. Forecasting is also an organizational, not only a technical issue. The Thesis provides a view for managers to handle and put in process demand forecasting in the healthcare services. The tools presented in this Thesis may help the manager in different ways to select and handle the demand forecasting. In the following, some potential managerial implications are introduced.

1. Implement the forecasting methods from the literature and then select the software tool for forecasting. It is also useful to notice the main trouble when implementing the forecasting practices and when defining the goals of forecasting, defining organizational responsibilities, and building effective performance measurement practices.

2. Plan the workload between different units and its doctors. Forecasting tool can provide information for the line management to schedule the holidays outside the high season.

3. Predict the need and capacity of the extra workforce and the use of rented doctors. One of these Thesis goals is to show for the organization when organization should try to react to the customer demand and employ more rented doctors to cover the demand overlap.

4. Develop the forecasting process for all the other business units as well as to start handle the customer demand more accurately.

5. Investigate and analyze some problems that occur in managing demand information in the healthcare such as
   Selecting the forecasting tools
   Explaining possible forecasting errors
   Enhancing the overall comprehension of the total forecasting process

6. Occupational healthcare center might provide the forecasting results for their outsourcing partner to better plan the possible overflow of the services that Occupational healthcare center cannot respond.

These recommendations made in this study are based on the analysis of the case unit and in the presented forecasting tools. They have also been influenced by relevant professional literature and the experience gained during this study. This Thesis proposes forecasts to be done by using SPSS Statistics 19 and its expert modeler as a forecasting model. This Thesis also suggests that OHCC start to conduct forecasts with other healthcare professionals such as nurse’s physiotherapists and psychologies. It is also recommended that introduced forecasting model should be escalated for the whole organization. The main managerial contribution of the implication is that when used correctly, they help managers to clarify the forecasting process in a resource-efficient way. The benefits of this study can be seen after running forecast side by side with current management system and governance. When running forecast side with current management system is easier to embed forecasting process to the whole organization. With alternative forecasting process, the organization can gain more knowledge of its customer demand.

The results for this Thesis are limited directly to the case company and for one selected business unit and this may limit the functionality of the model. The second limitation has to do with the extent to which the findings can be generalized beyond the forecasting models studied. The number of models is too limited for broad generalizations. However, the three different forecasting models represent rather different aspects of the forecasting process. Further empirical evaluations, however, are needed to replicate the findings in different contexts and surroundings. Also more forecasting accuracy indicators besides the R-squared method could be adjusted to the model.

For the follow up studies, this Thesis recommends that also as the data including age and sick leave data and diagnostic data should be investigated for the use of forecasting variables. It is also suggest for the follow up researchers to investigate and compare other statistical and judgemental methods. With alternative forecasting process organization can gain more knowledge of its customers demand. All though forecasting resources have to be in balance and in line to the organization and forecasting budget should not be exceeded therefore at forecasting is only providing help for the management decisions.

7 Summary

This Master’s Thesis builds a forecasting model for doctor´s appointments demand in the city of Helsinki OHCC in one of its selected business unit for its doctors and their customers.

In this Thesis the research methodology was based on forecasting theory and benchmarking models that already exist in science and business. Literature review introduced the forecasting theory and background for the organization to start to construct forecast for its selected forecasting target. At first healthcare organization has to get knowledge for its customer population and best available background information of its customers. Literature review also concludes that healthcare organization have to examine the existing variables that organization wish to use in the selected forecasting method. Organization has to construct and analyze the historical background data at least 2-4 year’s timeframe to navigate the trend and seasonality issues which occur in the provided healthcare service.

This Thesis presents different forecasting methods which are introduced in the literature. Forecasting literature has divided forecasting as statistical and judgemental forecasting methods. This study lists and introduces models for both statistical and judgemental forecasting methods.

The background of the time series forecasting such as ARMA, ARIMA and SARIMA forecasting methods which are used in this Thesis to perform the forecasts were presented in the Research Method and Material section.

Current status analysis of the case company customers provide information about customer age distribution, and other age related factors that Healthcare organization have to know about its customers, when starting to construct services for their customers and when starting to proceed forecast of its customers demand.

This Thesis has selected to use three different forecasting models to find out the best possible outcome for the organization to choose the best forecasting tool. Exhibited tools are Microsoft Excel Add-In, the SPSS statistics 19 SARIMA model and the same

products Expert modeler which has been selected as the forecasting tool for the case organization customer demand analyzes.
SPSS expert modeler combines both ARIMA and Exponential smoothing models and also considers the seasonality of the background data at the same time.

This Thesis proposes for the OHCC to conduct their forecasts by using SPSS Statistics 19 and its expert modeler because this model seems fitting in the background data and for to produce forecast. For the follow up studies, this Thesis recommends that for the use of forecasting variables the standard human resources data including age and sick leave data, and diagnostic data should be further investigated.

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Kysynnän analysoinnin kysymykset linjajohdolle

Miten näet osastosi palveluiden kysynnän

Miten näet että kysyntä vaikuttaa palveluiden tarjontaan

Miten näet että palveluiden kysyntä on muuttunut lähimmän kolmen vuoden aikana.

Onko jokin tietty osa-alue johon törmäät päivittäisessä työssäsi usein.

Koetko että tammikuusta huhtikuuhun ja syyskuusta marraskuuhun on kiireisintä aikaa työssäsi.

Miten näe terveyden huollon muuttuvan lähivuosina

Näetkö jotain muuta palveluiden kysyntään vaikuttavia olennaisia tekijöitä jotka koet tärkeäksi työssäsi.