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FORECASTING PATIENT VOLUME IN AN EMERGENCY DEPARTMENT USING TIME SERIES METHODS: AN APPLICATION OF A MEDICAL CENTER IN NIGERIA.

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ABSTRACT

FORECASTING PATIENT VOLUME IN AN EMERGENCY DEPARTMENT USING TIME SERIES METHODS: AN APPLICATION OF A MEDICAL CENTER IN NIGERIA.

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Institute of Social Science

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A time series is a categorization of data points, characteristically measured at a uniform time interval. We have time series in a variety of fields ranging from economics to engineering, social sciences to pure sciences. While analyzing the time series we use statistical methods.

Time series analysis (TSA) is a method used in analyzing data so as to extract its characteristics and use it to forecast into the future. The autoregressive integrated moving average (ARIMA) models belong to the category of linear models that are capable enough for discovering stationary and nonstationary series.

This study explores the application of the ARIMA models to patient volume (PV) in the emergency department (ED) of the Federal Medical Center (FMC), Kogi state, Lokoja, Nigeria. We thus, obtained monthly patient volume of this ED as a secondary data. Monthly patient volume between 2012-2016 were used as a training set, to decide on the proper values of model parameters. Up-to-date data for the first seven months of 2017 were used as a test data set to evaluate and compare the performances of the methods. In addition to generate forecasts for the total patient volume, two different approaches, indirect forecasting and direct forecasting, were used to forecast arrivals of male and female patients.

Keywords: Auto-Regressive Integrated Moving Average, Emergency department, Forecasting, Health planning, Patient volume, Time series analysis.

ÖZ

ZAMAN SERİSİ YÖNTEMLERİ KULLANILARAK ACİL SERVİSTEKİ HASTA HACMİNİN ÖNGÖRÜLMESİ: NİJERYA'DA BİR TIP MERKEZİ UYGULAMASI.

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Zaman serileri tipik olarak düzenli zaman aralıklarında ölçümlenen verinin sınıflandırmasıdır. Zaman serileri ekonomi, mühendislik, sosyal bilimler, soyut bilimler gibi çok farklı alanlarda karşımıza çıkmaktadır. Zaman serilerinin analiz edilmesinde istatistiksel yöntemlerden faydalanılmaktadır.

Zaman serileri analizi serinin incelenmesi, temel özelliklerinin belirlenmesi ve serinin gelecek değerlerinin uygun biçimde tahmin edilmesinde kullanılan yöntemdir. Otoregresif entegre hareketli ortalama modeli durağan ve durağan olmayan veri setlerinin analiz ve tahminlemesinde kullanılan linear bir modeldir.

Bu çalışmada, Nijerya, Kogi eyaletinin Lokoja ilinde bulunan acil servise gelen hastalara ait zaman serisi analizinde otoregresif entegre hareketli ortalama modeli kullanılacaktır. Bunun için hastaneden her ay bazında gelen hasta sayı verisi ikincil veri olarak temin edilmiştir. Uygun modellerin parametrelerinin belirlenmesinde 2012-2016 yılları arasında acil servise yapılan aylık başvurular öğrenim verisi olarak kullanılmıştır. Daha güncel olan 2017 yılının ilk yedi aylık perioduna ait veriler de uygun modellerinin performanslarının belirlenmesi ve karşılaştırılmasında kullanılmıştır. Aylık toplam hasta sayılarının tahmin edilmesinin yanında, erkek ve bayan hasta sayılarının tahmin edilmesi için dolaysız ve dolaylı olmak üzere iki bakış açısı kullanılmıştır.

Anahtar Kelimeler: Otoregresif entegre hareketli ortalama, Acil servis, Tahmin, Sağlık planlaması, Hasta sayısı, Haman serileri anal.

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Akeem Afolabi Salaudeen

Izmir, 2018

TEXT OF OATH

I declare and honestly confirm that my study, titled "FORECASTING PATIENT VOLUME IN AN EMERGENCY DEPARTMENT USING TIME SERIES METHODS: AN APPLICATION OF A MEDICAL CENTER IN NIGERIA" and presented as a Master's Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Akeem Afolabi Salaudeen

Signature

………………………………..

January 4th, 2018

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LIST OF ABBREVIATIONS

ACF: Autocorrelation Function.

ADF: Augmented Dickey-Fuller.

AR: Autoregressive.

ARIMA: Autoregressive Integrated Moving Average.

ARMA: Autoregressive Moving Average.

DF: Degree of Freedom.

DGP: Dynamic Grouping and Prioritization.

ED: Emergency Department.

ESI: Emergency Severity Index.

EW: Emergency Ward.

FMC: Federal Medical Center.

MA: Moving Average.

MAD: Mean Absolute Deviation.

MAPE: Mean Absolute Percentage Error.

MAUT: Multi-Attribute Utility Unit.

MSD: Mean Squared Deviation.

MS: Mean Squared.

PACF: Partial Autocorrelation Function.

PV: Patient Volume.

RMSD: Root Mean Squared Deviation.

SAR: Seasonal Autoregressive.

SMA: Seasonal Moving Average.

SS: Sum of Squares.

TSA: Time Series Analysis

1. CHAPTER INTRODUCTION

Forecasting which is one the tools used for planning, and has been in existence for more than a decade. Organizations uses it in their efforts to manage the unpredictability of prospective events e.g. Dangote flour mills and cement factories uses it to forecast demand and even bakeries use it for predicting demand. Forecasting is mainly subjected to past and present analysis of data. It is also one of the most important instruments in making swift decision, which is used by all businesses, assisting them in budgeting, planning and estimating future developments. In the simplest expressions, forecasting is the efforts put in envisaging future outcomes based on historical events and administrative perceptions. Although, forecasting uses previous data in determining in what trend it will be following into the future. In fact, it is normally used by businesses in deciding how to distribute their resources or to plan for projected expenses for an impending duration, and of which it usually depend on the projected goods and services demanded by consumers which the businesses have to offer.

Furthermore, the process of predicting starts by means of some speculations that are based mainly on the administrative experiences, information and decision. Speaking of which, these expectations may contain errors with outcomes of similar mistake in forecasting. Then the procedure of sensitivity analysis can now come into play (Predicting the outcome of a decision, given a clear set of variables, which can be determined by forecasters on how changes in a particular variable can influence the outcome of forecasting). Therefore, these estimates can be projected into the imminent periods of making use of different methods such as Box-Jenkins model, exponential smoothing, moving averages, Winters' method, regression analysis, trend projection and so on.

Forecasting plays an essential role in the set-ups of modern day management. It facilitates planning and these plans are the pillars for effective operations in organizations and even businesses (small, medium or big businesses). A lot of establishment have been unsuccessful due to the lack of forecasting or even ineffective forecasting which relies more on planning than not. E.g. Curtiss- Wright, a major airplane builder, in conjunction with the likes of Douglas and Boeing in the early 20th century, a decision was made to gamble their money on improving the piston engine rather than jets. Curtiss-Wright organization did not predict precisely what will be the market for jets in the future and because of that they were unsuccessful. Therefore, the more precise the future situations can be foretold, the greater and sophisticated the probability of accomplishing these well laid strategies will be. Forecasting implicatively suggests that the act of constructing a comprehensive investigation of the future and orchestrating inconceivable plans without either foretelling the future as accurately as possible or making insightful speculation about it.

Forecasting can be perceived as the preparation of deliberately well-thought-out decision built on sentiments, thoughts and understandings, and these judgments, at best could well be ignorant speculations. It could additionally be established through a logical study and analysis of appropriate data and this process can be called “analytical forecasting”. This will be subject to a study of past occurrences and present situations with an assessment of illustrative reasoning and making conclusions about imminent occurrences.

Since forecasting has been in existence for quite a long time, it is now a very important tool in almost every major area of our lives, forecasting could well be used personally and it can be used in big firms or companies and industries such as hospitals to predict patient volume on a daily, monthly or even yearly basis etc., educational institutions e.g. schools use forecasting to predict the number of students that will be granted admission into their schools and it is used by businesses to predict the future environment for operation and it is also a necessary aid for planning. Some of the areas in which precise forecasts for future events and trends are compulsory for organizational prosperity and intensification are; developing the economy, technological forecasts; forecasting competition and social forecast.

In spite of the basically inaccuracies in attempting to forecast what the future hold, forecasting helps us in policies and development settings. For example, Federal Reserve Board try to adjust the interest rate by projecting into the future, the economic growth and the pressure of inflation in a country. Furthermore, operations managers prognosticate future sales of the company and also prepare production schedules. Companies also try to determine the number of staffs for its call centers by forecasting the demand for services and hospitals uses it to plan staff schedules and manage medical resources and also to forecast patient volume, while banks use forecast for planning future bank deposits such as money and other valuables e.g. gold and loan balances i.e. credit card debt.

Method of forecasting is a way of generating forecast from past and present values. Forecasting usually arises from the identification of a particular model for the data and try to determine the optional forecasts conditional on that model. Categorically speaking, there are three main methods of forecasting namely- judgmental forecasts, univariate and the multivariate methods. They are briefly explained below as follows:

1. Judgmental forecasts: these are basically built on instinctive judgment, perception, ‘‘insight’’ viable information and further necessary existing evidence.
2. Univariate methods: this comes in handy when predictions rely solely on current and previous values of a sequence been prognosticated perhaps increased by the outcome of time e.g. trend.
3. Multivariate methods: here, the unpredictability of a forecast depend slightly on values of single or additional variables of time series analysis, known as the forecaster or the descriptive variables.

Emergency department (ED) of a hospital is in charge of providing medical and other similar care to patients received at the sickbay in need of instant or quick medical attention. ED is also known as the accident and emergency zone, emergency clinic, emergency surgery. All of these names imply where patients in need of emergency care or immediate care are been admitted in for immediate treatment as was mentioned earlier, but most of the time without any prior appointment. It is one of the most important part of a medical health center or a hospital which assesses and gives treatment to patients with serious injuries or illness. It is mostly open 24hours a week and 365days a year, which makes it an important place where a lot of money should be invested and it could be owned privately or publicly i.e. owned by one person, group of people and or even owned by a government.

As was previously mentioned, that ED is one of the most important part of a hospital and it is where most of the time, patients’ journey begins and it is also the front door to most hospitals around the world, it may as well be the connecting and catalyst point for patient care coordination. ED is as important to patients and families as well as to hospitals and health systems. It is equally important in the following ways:

1. It serves as a hub for pre-hospital emergency medical systems.
2. It serves as an acute diagnostic and treatment center.

3. It serves as a primary safety net.
4. Open 24hours a week and serves as a portal for rapid impatient admission.

Forecasting is used by every business around the world including in the healthcare centers, most importantly in the emergency departments. ED uses forecasting to predict the surge in the patient volume (PV) i.e. the increase in patient volume. Consequently, the important use of forecasting in the ED are as follows:

1. To forecast ED crowding.
2. To forecast ED overcrowding.
3. To forecast PV (hourly, periodically, daily, monthly or even yearly).
4. To forecast the length of stay and acuity.

As a result, emergency departments (EDs) uses forecasting to reduce cost, to manage their resources efficiently, to increase patient's satisfaction, to increase both patients and staff's safety, to increase service quality, to increase public health safety, to increase welfare to mention but a few.

Subsequently, there are several reasons for applying forecasting method in the EDs but the most important reason is to aid resource planning. The resources in the ED are the doctors, nurses, technicians, cardiologists, midwifery, physicians, drugs as well as all the technological equipment and the non-technological equipment used in the ED which is used at the micro level of EDs, but at the macro level of EDs, forecasting methods are used for financial and strategic planning.

Nigeria population is approximately 193,798,602 making it a considerable size of black nation in the world. And male population with an estimate of about 98,135,280 (50.6%) and female population with an estimate of about 95,663,344 (49.4%). The Federal Republic of Nigeria, has its area covered with an approximately 356,669 square miles on the West coast of African continent. To the east is the Republic of Cameroon, to the while Niger Republic is to the north and to the west is Benin Republic. In the northeast, there is a 54-mile elongated boundary with Chad Republic, while the Gulf of Guinea seashore is extended for more than 500 miles from the west of Badagry to east of Calabar, and consist of the Gulfs of Benin and Biafra. Today, Nigeria has thirty-six states and capital including the Federal Capital Territory Abuja.

Data was collected in a hospital in Lokoja, Federal Medical Centre (FMC), the capital city of Kogi state in Nigeria, home to about 3million people. It has a population of over 195,000 people consisting of a male population of over 100,000 (64%) and a female population of over 95,000 (36%) in total. Kogi state, widely known as the confluence city mainly because of the coming together of the two rivers Niger and Benue in the capital city of Lokoja, which was the first administrative capital of Nigeria.

Consequently, the goal of this dissertation is to forecast PV in the emergency department of the hospital, while making use of the past data to generate forecast of patients arriving into the hospital for better future plans. Undoubtedly, there are lots of different time series methods which was used in different kinds of study (few were mentioned in the literature review) to forecast PV, the extent of stay and acuity for an ED and for predicting the days when the hospital will admit a whole lot of patients.

Finally, our objective is not to setup the probable roots of ED crowding and overcrowding but to offer a universal theoretical background which can be used to find the time series forecasting method to forecast patient arrivals into the hospital's ED and to be able to manage the little available resources at the hospital's disposal. Furthermore, we develop a univariate Winters' method for predicting ED demand using data from FMC as was previously mentioned and afterwards we compare the data to the autoregressive integrated moving average (ARIMA) models. Furthermore, we will use the 7-months testing data set to forecast for male and female patient arrivals using the direct and indirect methods of forecasting. This study was written having it at the back of our mind that this method will be applied in the ED hospital settings, but it is not limited to only this kind of scenario.

The following is the plan of this thesis; Chapter 2 presents the literature review on emergency medicine, forecasting and time series methods. Chapter 3 presents detailed analysis applied on the secondary data collected from FMC. Chapter 4 presents the results of our time series methods and the method comparison and Chapter 5 includes discussion and the conclusion part.

2. CHAPTER LITERATURE REVIEW

Over the years, modeling and forecasting have been providing useful information for a lot of different organization's management, it can also be used in medical centers for allocation of resources, setting up staff rosters including holidays as well as planning future expansion (R.E. Abdel-Aal and A.M. Mangoud 1998).

ED, as was explained earlier, is the main arrival path for patients into the hospital and patients in need of quick emergency care. The inflow of patients into the hospital cannot be booked or controlled i.e. patients arrive in the hospital ED without prior notice. Arrivals increases on many time scales due to the periodic effects or temporary tragedies, in the wake of busy times, especially in the developing countries, for example, Nigeria, EDs suffers operational crisis that put patients at high risks in so many ways e.g. some patients might not receive treatment on time which might lead to dangerous situations (Jeffery K. Cochran and Kevin T. Roche 2008).

Recent researches suggest that the output factors (number of casualties put on hold and waiting to be admitted into the ED) which also varies considerably across ED sites should be seen as also a problem. The ability to allocate ED casualties to inpatient beds of which the admitted patient casualties staying in the ED are the main issue that needs solving before admitting new patients into the emergency department inpatient beds (Moskop et al., 2009).

Therefore, the ability to forecast i.e. predict ED visits (input component) is quite crucial for both medical teams and ED administrators as they could both benefit from accurate predictions to optimize planning and support strategic decisions making. Though, there are other researches that have also tried to accomplish this goal, with the most commonly used procedures such as regression models, heuristic forecasting, artificial neural network forecasting, Winters' method and time series analysis. (J. Berg et al., 2014; Tandberg and Qualls, 1994; Milner, 1997; Champion et al., 2007; Jones et al., 2008; Schweigler et al., 2009; Sun et al., 2009; Wargon et al., 2009).

2.1. Emergency Medicine

Emergency medicine, formally known in some countries as trauma and accident department stand as the medical field of study consisting of care for proportionate and unscheduled patients with ailment or injuries requiring urgent medical attention. (Umia, University of medical services).

Emergency medicine (EM) has developed in its field and task fulfilling a crucial or important part in the safety of patients in several nations. Recently, development, elderly, financial fluctuations, and deteriorate well-being difficulties have led to a bigger understanding and the need for urgent attention to healthcare all over the world. EM is now more significant mainly because of its ability to cater for our everyday therapy or medication wants, and also for provision of preparation and control of catastrophe. There are over 20 countries that recognizes EM for its specialty and there are also countries where it is not yet recognized for example in the developing world. Therefore, many of these countries are trying to follow the trend of such concession so as to develop placement tutoring scheme as such. There are still many countries without this specialty but are working towards developing it and they are trying to reach out to other countries with success and flourishment in this specialty of EM. This allows for medical doctors from thriving countries that are quite dynamic in the administration of representing EM for the provision of enlightenment for the expansion of emergency healthcare schemes, program advancement, aptitude test, placement instruction and study in the developing nations. (Kumar Alagappan et al., 2007).

Emergency rooms were first established in the 20th century, in order to address the increasing need for medical diagnosis and treatment in critical situations. Nowadays, hospital EDs around the world provide primary health care to patients whose illnesses or symptoms require instant attention and in some cases, may be life frightening. As was previously mentioned, some countries EDs function similarly to EDs in the developed world like the United States and in Europe. Specifically, when a patient arrives at the ED, he or she goes through an initial triage examination, in which a nurse checks the vital signs, runs tests as necessary and categorizes the patient according to his or her condition. The classification process may vary somewhat across hospitals, in particular, it may vary between private and public institutions. But in most cases, it is related to the Emergency Severity Index (ESI) decision method, in which patients are sorted and prioritized on the basis of the urgency of treatment and the quantity of resources that treatment is expected to require. In recent years, many significant improvements to the Emergency Severity Index (ESI) have been proposed e.g. Utility Theory Based Patient Sorting, Multi- Attribute Utility Theory (MAUT) and the Dynamic Grouping and Prioritization (DGP). ED in hospitals around the world try to refer to a general classification method resembling the Emergency Severity Index (ESI), in the order in which patients are received and treated is determined by the degree of urgency and severity of their respective medical problems and not necessarily by order of arrival. Patients who necessitate urgent treatment are prioritized over patients with less severe symptoms. After initial examination and emergency treatment if needed, patients are either transferred to one of the areas within the ED, hospitalized in a department of the hospital, transferred to another hospital for various reasons, or discharged. (Amir E., Guy W., 2015).

The crowding of ED is a situation that was initially reported over ten years ago and has resurfaced as a prevalent and increasing situation all over nations worldwide. Numerous writers report that the recent problems in the EM work, a point of view very common in different reports that state that the surge in the ED is quite similar to a superior supply and demand contradictories inside the medical health center, mostly known by the deficiency of huge volume of patient's inflow in some country's infirmaries. The way the number of ED visits and ED crowding is growing at an alarming rate is giving concern, which has negative effect on the standard of medical care and as a result potentially dangerous or harmful events can occur. The situations that are concerned with the standard of medical care and the safety of patients make ED administrators even more anxious to find a long-lasting solution. As a result, ED find themselves in a very difficult and challenging situation and circumstances. (Collis, 2010., Moskop et al., 2008, 2009., J. Bergs et al. 2014).

Furthermore, emergency department crowding is a serious hurdle in getting a quick medical attention in some nations. Patients in the EDs frequently witness a lengthy waiting periods before they get treatment and those in need of urgent admittance do have to wait even much longer than expected because of occupied inpatient sickbay bed. Therefore, because ED crowding is an image of a huge demand and supply disparities in the medical system this makes these problems even more harder to solve by isolating ED crowding. Therefore, to find a better and long-lasting solution. There is need to study emergency department crowding in the setting of a complete supply scheme by making use of dependable procedures to comprehend, evaluate and observe the size of the system (Brent R. Asplin et al., 2003).

There are some potential definitions of ED crowding and also some suggested influences which are likely to be instrumental to these issues. Schull and the others made use of a board of professionals to try and identify the significant factors of ED crowding. A speculative model was established by them for ED crowding by categorizing the likely sources of the surge into ‘‘four’’: ‘‘public’’, ‘‘victim’’, ‘‘emergency department’’, and ‘‘hospital determining factors’’. Ambulance diversion was identified as one of the most convenient active classification and illustrative volume of controlling ED crowding. However, the reason why the diversion of ambulance is not a possibility for some healthcare centers, and because EDs have a vast inconsistent conception for ambulance diversions. Therefore, generally speaking, the definition of ED crowding is not applicable to some countries. Schull and the others dismisses the issues such as the accessibility of elementary health care centers in rural areas as a significant factor of ED crowding which is quite often seen in the developing world e.g. Nigeria (Brent R. Asplin et al., 2003).

Some few years back, serious overcrowding in the EDs became an international issue. Although there was a temporary improvement on the problem just for the time being, the problem facing the ED overcrowding has reemerged and it is threatening to grow disastrous day-by-day. Overcrowding is triggered by the intricacy of interconnected problems which has been outlined in various articles. Too many patients in too little space subjected to inefficient procedures. This is the essence of overcrowding in the ED. Since 1975, the number of hospitals has declined from over 7,000 to about 5,700. Hospital bed volume chop down during the same period from 1.5 million to fewer than a million. Meanwhile, the number of ED visits has increased almost every year, totaling 136 million by the year 2011. The resulting formula for overcrowding is obvious: fewer hospitals + fewer beds + increased ED visits = overcrowding. 90% of hospitals experiences overcrowding at some point. The practical consequence of overcrowding is boarding – when patients are kept in the ED for hours or days after the decision to admit them has been determined (Thomas Syzek, 2017).

Overcrowding in the emergency department has many effects on patients, such as leaving victims of accident at risk, some patients having to go through lengthy sufferings, patient waiting for a long time, patient discontent, diversions of ambulance around zones, reduced medical doctor output, frustration amongst health staffs, and even breaking out of violence in the hospital environment. To solve the issue of congestion in the hospital it will require a lot more than financial dedication from the government but will also require the collaboration of Medicare. Except a solution is fashioned out to eradicate this growing problem of overcrowding, the community may stop depending on EDs for good and quick emergency care, placing people all around the world at great risk (R.W. Derlet, J.R. Richards., 1999).

Furthermore, ED overcrowding is becoming a persistent problem around the world, however, under the perfect circumstances, there is availability of emergency care for patients with critical conditions. Therefore, the preliminary assessment and balancing of patients who requires emergency care can take up to 2hours. Prompting the discharge of patients with minor problems to be hasty and the ones in need of additional assessment and care are admitted for treatment. In some parts of the world, overcrowding occurs when patients in need of admission cannot be admitted into the ED for the reason that inpatient beds are not available. Hence, when such patients occupy the ED, it is the duty of emergency medical doctors and nurses to provide inpatient and emergency care concurrently for a prolonged duration. This extremely compromises their capability to make arrangements for the new emergency patients arriving at the hospital. Also, a huge number of patients with lengthy stay is one of the main difficulties they come across in their day-to-day practices. For these reasons, some patients favor going to community hospitals in their various countries, in the hope of receiving quick and better medical care there (Fuh-Yuan Shih et al., 1999).

In the meantime, some critically sick patients are sometimes declined care or even are sometimes by-passed by these community hospitals because of the insufficient financial reimbursement. This is a scenario which is quite common among the developing countries; e.g. Nigeria. This problem cannot be overcome so easily by mere hard work, so, therefore, procedures which includes effective commitment and the involvement of community efforts have been put into action, nonetheless, no positive impact on the problem. Though, by evaluating the period and reducing the lengthy stay in the hospital ED, we can try to improve the problem by urging the medical healthcare administrators to implement the required schemes to enhance the standard of ED patient health care systems in some parts of the world where the problem persists, especially in the third world countries (Fuh-Yuan Shih et al., 1999).

Some of the most common causes and effects overcrowding has on the emergency department are: huge complication of patients presents in the ED, general upsurge of patient arrivals, few nursing staff for huge number of patients, few clerical support staff and slow services rendered by the laboratory and ancillary services. These causes were indicated by stating that some of the lists of ED overcrowding resulted from various composite and usually connected issues which may have caused the changes in EDs. And it has also lead to diminished physicians' output and effectiveness. These are some few lists of how overcrowded situations in the ED may have resulted in a number of different effects which are: risking the wellbeing of the community, long waiting time, diversion of ambulance, ineffective physicians and miscommunication due to noisy and congested environment (R.W. Berlet and J.R. Richards., 1999)

With all the aforementioned facts, about the ED crowding and overcrowding, and how they both affect the hospital's internal management and also lead to mismanagement of resources and patient dissatisfaction. There are several ways of preventing such circumstances in hospital's ED, such as using forecasting methods to predict into the future the number of patient's arrivals into the hospital's ED.

2.2. Forecasting

The process of forecasting is used for evaluating predictions using past and present data, as was previously mentioned. It can basically be an algorithm regulation which may not be subject to the original possibility model. Possibly, from a different point of view of categorizing a specific model for a data and detecting the ideal predictions depending on the sample. Hence, the words ‘‘method’’ and ‘‘model’’ are obviously different from one another but unfortunately the ‘‘projecting model’’ is used quite often times in some research and it is mostly wrongly used instead of predicting method (Chris Chatfield., 2000).

There have been lots of studies on the prediction of ED hospital arrivals recently. The earliest emergence of such work was by Milner, presented an ARIMA model forecast for the total arrivals into the emergency department. The work of Milner paved way for other researchers to be attracted to generating lengthy model predictions for ED patient influx, many of them made use of time series models such as the (autoregressive integrated moving average) ARIMA model and the autoregressive moving average (ARMA) model, as well as Winters' method as they proved to be quite effective in forecasting (Milner., 1988; Kadri et al., 2014; Sun et al., 2009; Jones et al., 2002;

Shi et al., 2011).

Furthermore, forecasting short term models were also examined by many studies, they used techniques such as ARIMA, linear regression, exponential smoothing, and the Monte Carlo simulation based models. There were other studies interested in developing the set of peak periods demand for a pediatric division (children in need of treatment) of the ED in Lille, France (Abraham et al 2013; Ekstrom et al 2013; Bergs et al. 2013; Mielzarek 2013; Bouleux et al., 2014).

Meanwhile, there are articles that were interested in getting ahead of the difficulties of the EDs patient flow, and they were all considered big phenomenon of their time and are quite similar because most of them are based on a crucial and unforeseen human needs. Categorically, there are researches that showed interest in predicting short-term emergency provisions, making use of radial basis function of neural network (Mohammadi et al., 2014; M. Afilal et al., 2016).

And finally, forecasting the number of ED appointments at a time frame is quite a tough task to take on. Therefore, mismatching emergency department patients with staffing may result in ED crowding and can also lead to low performance of the emergency department, as well as increasing patient dissatisfaction. Which may also affect the transition of patient from the emergency department to the floors where patients who have already received treatments stay. Mathematical models are normally used to forecast the number of patients visiting the ED and it has helped in developing some previous models which were commonly used. Such as linear regression or time series models, which include days, weeks or even months of the year and climatic data, as forecasting determinants. Even though some studies show that the daily data of the week is the strongest predictor for ED patient inflow, but in our case monthly data are being used for forecasting EDs patient volume (Andreas Ekström et al., 2015).

So, since we collected data on a monthly basis, we cannot use the daily data collection effect because it will not be suitable for our model. However, we will be making use of the monthly PV for short-term forecasting and which has also been used by many studies. Also, there are several models about the amount of patient volume for predicting trends for long-term use and therefore making them inappropriate for daily modification of ED employees. So, a model for predicting ED patient visits and at the same time enabling better scheduling of medical staffs and ED patient visits and also increases throughput to avoid patient influx. This can, in the long run help strengthen the safety of patients, by making use of independent variable which are relied upon by earlier researchers in the field. Several methods of forecasting such as moving averages, exponential smoothing, Winters' method, heuristic methods etc. have been used by different researchers in different literatures to forecast patient volume in the ED. But methods such as ARIMA, Winters' method, Holts method, time series methods and ARMA seems to be the most commonly used out of all these forecasting methods (Leslie S. Zun., 2009; Andreas Ekström et al., 2015., Bergs et al., 2014; Jones et al., 2008)

2.3. Time Series Methods

Time series is a compilation of results that were successively and characteristically equal in different time frame. The unique attribute of time series analysis in reality is that the analyst must consider the time sequence since the observations are frequently not autonomous. Whereas other statistical concepts are concerned with the random models of the autonomous investigations. The methods of evaluating time series can be seen as a significant area of statistics. Also, time series is a sequential outline of sets of data, usually estimated at systematic periodic intervals. Time series analysis includes strategies for evaluating time series data so as to seperate relevant attributes of the data and predicted values. Though there are numerous objectives used in fulfilling a time series by analyzing it, and they can be categorized as graphical, clarifying, forecasting, or direction (Box, G.E, Jenkins, G.M, Reinsel, G.C., 1994, and Shakira Green., 2011).

Time series are frequently scrutinized in the hope of ascertaining a past model used in subjugating prediction. For us to identify this model, it is appropriate to reflect on the time series that comprises of different components and by so doing, a descriptive approach is necessary. Time series components are trend, cyclic changes, seasonal variations and inconsistent circumstances (Diana-Mihaela Pociovălişteanu., 2008).

The pattern of change in the mean level is considered an essential development or deteriorating elements in the series. The periodic elements are apprehensive with the seasonal variation in the series year-by-year. Seasonal variations are practically regularly attributed to climate transformations. This kind of technique where there are variations in a year period such large portions of variations are frequently seen in time series for sales and also temperature analyses. Cyclic transformations in a time series are comparable with the seasonal elements that will be seen oscillating up and down. Cyclical variations are believed to vary differently over a stable duration mainly because of some concrete reasons except for the recurrent outcome.

Sequences are usually limited to a specific stable duration and can occur almost every year. The moment we have accounted for the trend and cyclic fluctuations, the rest of the variation is ascribed to an unbalanced variation and as a result of the data there exist a series of residuals. This set of residuals are not random, so therefore, the residuals are evaluated to ascertain that all the cyclic variation have been eradicated (Chatfield, C, 1989, Shakira Green, 2011 and Diana-Mihaela Pociovălişteanu, 2008).

However, during the evaluation of a time series, a significant action is to be taken in plotting the reviews in contrast to time series. The line segments are merely not for exaggeration, but for supporting the continuous time scale that exists in the graph. The plotted time series is normally used to acquire the basic illustrations of the main characteristics of the series. And this plot can instantly disclose its features such as trends, seasonal variations, interruptions, and irregularities that can be found in the data (John E. Hanke and Dean Wichern., 2014).

As was mentioned earlier, the key importance of time series is for forecasting into the future. In the case of dependent subsequent opinions, imminent values are usually predicted from historical investigations. If the imminent values of the time series can be precisely predicted then times series can be classified as deterministic and it is frequently noted that these forecasted values can only be partly derived from historical findings ((John E. Hanke & Dean Wichern., 2014, and Shakira Green., 2011).

A time series is also a progression of observations taken sequentially in time. Data sets are seen as the series, for example, the series of the number of monthly commodities dispatched from an industry, the series of the weekly number of highway tragedy, the amount of daily snowstorm etc. time series are commonly used in educational fields such as, economics, business, engineering, the natural sciences and even in the social sciences. (George E.P. Box; Gwilym M. Jenkins et al., 1988).

Time series analysis (TSA) is a beneficial tool for forecasting the variations of numbers over a specific period of time, e.g. volume of patient entering into the emergency department. And as a matter of fact, these models are used when estimating how the array of observations will pan out in the future. Time series model make use of information on the factors influencing its behavior, they will then extrapolate trends and seasonal patterns, but ignore all other information such as weather, flu outbreak. The precision of time series model render forecasting more useful than the regression model. The forecasting methods used by time series are, ARIMA models, Winters' method, exponential smoothing and structural models (George E.P. Box; Gwilym M. Jenkins et al., 1988; Shakira Green., 2011).

TSA and forecasting are broadly used in businesses for strategic planning and administration. Though, TSA is used in hospitals around the world but is limited, for example, Wargon and the others found some studies on emergency department forecasting in some scientific assessment that few of those studies used TSA while the rest of them used the generalized linear regression models. (Patrick Aboagye-Sarfo et al., 2015).

The analysis of time series is uniquely for determining the comportment of the series, i.e. detecting trend, seasonal or cyclic development. And it is used explicitly in the pattern of trend, seasonal or cyclic movement in observing its performance, in the economy, and the effect the world has on the data. It could also be used for forecasting, which will be the main purpose of using it in our study. For it to be easy to fabricate a model for the series, the forecaster must first and foremost know that there is a lot methodology used in modeling and that there is no particular method for every circumstance. Only the ARIMA models offer numerous alternatives. The forecaster needs to be conversant with the different models existing for each process, but also be mindful when each procedure can be used in forecasting. The autoregressive integrated moving average (ARIMA) models, or Box-Jenkins methodology and Winters' method are all capable of depicting stationary and nonstationary time series data and belong to the class of time series models. (Box, G.E, Jenkins, G.M., and Reinsel, G.C., 1994).

Therefore, since time series provide an acceptable performance which has been widely used by previous researchers, even though we will be using time series methods such as ARIMA models and Winters' methods for forecasting the amount of patient arrivals in a hospital ED in a developing country like Nigeria, making it one of the very few researches in the country that has made use of time series methods.

2.3.1. Winters' Method

Winters' method generally belongs to the class of time series models used for forecasting and it is one of the most commonly used methods of forecasting.

Winters' method also known as the exponential smoothing that is modified for trend and seasonality, it is also an extension of Holt's method. Holt's method makes use of only the trend while Winters' method preferably uses both trend and the seasonality, as was previously mentioned. It also employs three smoothing constants to forecast or predict time series data for level which is the alpha (α), for trend which is the beta (β), and for the seasonality which is the gamma (δ) (John E. Hanke and Dean Wichern., 2014 and R.E. Abdel-Aal and A.M. Mangoud., 1998).

Winters' method which could also be regarded as the triple exponential smoothing method, because of its use of the three-different smoothing constant as was listed above. It is also a method for projecting the future, provided that the series is ''seasonal'' that is repetitive over some period like in our data.

Haven said earlier that Winters' method is a three-parameter linear but it is also a seasonal exponential smoothing and an extension of Holt's method used in representing data set and also diminishes forecast flaws and the two forecast methods known as additive and multiplicative methods. But in case of our data, due to the variations, multiplicative method was employed.

As shown in equation 3 below that in computing the existing seasonal element, S_t, the output of γ and an estimation of the seasonal index given by Y_t/L_t is added to $(1-\gamma)$ multiply by the former seasonal factor, S_{t-s}. It is a procedure that is correspondent to the smoothing existing and preceding values of Y_t/L_t. Y_t which is separated by the present level of the estimate, S_t, through the creation of a ratio which is useful in a multiplicative method to modify a forecast so as to have a cyclical spikes and troughs (John E. Hanke and Dean Wichern., 2014 and R.E. Abdel-Aal and A.M. Mangoud., 1998).

(Level): $L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1})$ ……………………….............................(1)

(Trend): $T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$ ……………………………………………… (2)

(Seasonality): $S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s}$ …………………………………………………... (3)

Where:

L_t = current estimated level

α = smoothing constant

Y_t= actual value in t period

β= smoothing constant trend

T_t= trend estimate

γ= smoothing constant seasonality

S_t= seasonality estimate

And $\alpha,\ \beta^*\ and\ \gamma$ are constants interpret as $0 \leq \alpha \leq 1$, $0 \leq \beta^* \leq 1$ and $0 \leq \gamma \leq 1 - \alpha$, where as m is the seasonality period and Y_t is the emergency department patient volume series.

2.3.2. Autoregressive Integrated Moving Average Models

The autoregressive integrative moving average (ARIMA) models belongs in the categories of time series models too just like Winters, and it possesses the potential of illustrating stationary and nonstationary time series. ARIMA does not exist in an autonomous variable when constructing them. However, they generate forecast on their own through the usage of information found in the series. E.g. ARIMA models for daily transactions will be determined by the past transactions pattern for producing a forecast that will show the following month's sales.

ARIMA models most of the time reckon more on autocorrelation models in the data collected, while the Box-Jenkins technique is more suitable for identification, estimation, and diagnostic examination of the appropriate ARIMA models. It has also been in use for quite a long time but its first appearance dates back to the year 1988 when it was first introduced by Milner. And since then many researchers have been interested in the ARIMA models as was explained earlier on in our study.

ARIMA model comprises of three main components. The first component which is notated by AR shows the autoregressive part, and depends on the past values of data set. The model parameter of this component is represented by p. While the third component is notated by MA and it shows the moving average part. The structure of this part depends mainly on the errors terms and not on the past values. The model parameter of this part is represented by q. Finally, the second component is the integrative part which relies on the differencing of un-stationary data series. The differencing parameter is represented by d in the model. Thus, the ARIMA (p, d, q) model is given as:

$(1-\sum_{k-1}^{p}\alpha_k L^k)(1=L)^d X_t = (1+\sum_{k-1}^{q}\beta_k L^k)\,\varepsilon_t$ .... (4)

But based on our data set, one or more parts of the ARIMA models can be inactive. For example, if the data set is stationary, then the differencing part will be inactive which means that related parameters will be equal to zero. i.e. $d=0$. Then the model is converted to ARMA (p,q). The detailed properties and structures for the main components will be presented in the next sections.

2.3.2.1. Autoregressive (AR) Models

Autoregressive model is also one of the components of ARIMA model with the acronym AR model. It is quite appropriate for depicting some virtual series that are reoccurring, known as the autoregressive model. In this model, the existing value of such process can be seen as a fixed, linear model of previous values of such process and some irregular shock. AR also captures the past data of the time series.

In this autoregressive process of the order of p, the observation Y_t is generated by the weighted average of the past values rather than the current values. In time series (Y_t) is an AR process with order p of (AR (p)) if each and every observation Y_t of AR (p) process can be represented with the following equation:

The autoregressive model of pth-order:

$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t$ .... (5)

i.e. $\widehat{Y_t} = Y_t - \varepsilon_t$

Where:

Y_t= dependent variable at t time

$Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$= response variable at time intervals $t-1, t-2, \dots, t-p$, repectively; the $Y's$ are the independent variables

$\phi_0, \phi_1, \varphi_2, \dots, \phi_p$= coefficients in need of estimation

ε_t= error term at t time, representing the unexplained outcomes of the variables; therefore, the theory behind the error term and the standard regression model are in the same bracket.

2.3.2.2. Moving Average (MA) Models

Moving average is also a time series model with the acronym MA. It is actually another type of model that uses the process of the order of q. The moving average process is an immense standard application in actualizing the analysis of time series. MA part does not capture the past data but it does capture the errors of the model.

The moving average model qth-order:

$$Y_t = \mu + \varepsilon_t - \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2} - \cdots - \omega_q \varepsilon_{t-q} \quad (6)$$

Where:

Y_t= dependent variable at t time

μ= constant mean of the technique

$\omega_1, \omega_2, \dots, \omega_q$= coefficient in need of estimation

ε_t= the error term representing the outcome of the variables is not interpreted by the model; therefore, the theory behind the error term and the standard regression model are the same.

2.3.2.3. Autoregressive Moving Average (ARMA) Models

Many stationary random procedures cannot be modelled as entirely AR (p) or as completely MA (q) primarily because they possess the characteristics of both types of procedures. A model with AR terms in unification with a model that has MA terms to get a ‘‘mixed’’ ARMA model. It is convenient when using the notation for ARMA as (p, q).

Where:

p: order of autoregressive

q: order of the moving average

So, the general form ARMA models (p, q) the equation is below:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t - \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2} - \cdots - \omega_q \varepsilon_{t-q} \quad (7)$$

Where $\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}$, ... are uncorrelated with one another.

ARMA (p, q) can be used in describing stationary time series with variations. Generated forecast by the ARMA (p, q) will be subject to existing and historical values of their replies. While differencing involves figuring out the differences at intervals of subsequent investigations of the time series till it changes to a stationary series. For non-seasonal data, integration is generally acceptable so as to achieve the stationary series, for the contemporary series based on $(\chi_1 \dots \chi_N)$ can be expressed as $y_t = \chi_{t+1} - \chi_t = \nabla\chi_{t+1}$.

2.3.2.4. Executing ARIMA Models for Seasonal Series

A data that is seasonal has a different pattern and repeats itself year in year out i.e. a monthly data that shows an annual seasonal pattern for the same months of different years must correlate. E.g. January in one year should be similar to January in the following year and so on. That is to say, seasonal data has the characteristics of repetitiveness. Thus, not only the observations within the year are similar or related to one another (correlated) but also observations over the years are similar to one another (correlated). Furthermore, if the length of the seasonal period is S, so that monthly data $(S = 12)$ and quarterly data $(S = 4)$. The autocorrelations and partial autocorrelations for seasonal processes are non-zero at low lags (within-year association) and at lag that are multiples of the seasonal period S (between-year association). Therefore, both interpretation of the autocorrelations and partial autocorrelations at the seasonal lags will be the same as the interpretations of autocorrelations and partial autocorrelations at low lags (George E.P. Box; Gwilym M. Jenkins et al., 1988, M, Wargon; B, Guidet; T D Hoang; G, Hejblum 2008).

There are four elementary stages of forecasting methodology using the Box–Jenkins technique: First stage: Clear identification of a model through the observation of the performance for stationary time series values. Second stage: The use of historical data to evaluate the clearly identified parameters is necessary. Theoretically, least squares can be used to generate parameters but since non-linear least squares algorithms regularly contain the integration of search procedures that requires implementation, therefore, this stage requires computer programs for it to be accomplished. Third stage: Box-Jenkins modeling technique is used to check the diagnostic. A diagnostic check is done to verify the model or to check if the model needs amending. A ‘‘good’’ model must have the following characteristics such as: residuals should be approximately normal, estimates of parameters should have significant P-values and the model should consist of few parameters. Fourth stage: This is the stage where the model is used for forecasting (Box, G.E, Jenkins, G.M, Reinsel, G.C. 1994, and Shakira Green., 2011).

The technique used for the non-seasonal series can as well benefit from the seasonal time series data, which could be useful as we move forward in our study. Like the seasonal data, constant differencing has to be applied so as to make the non-seasonal part of the series stationary. Seasonal differencing is however required for the seasonal part hence making it stationary too.

As opposed to regular differences taken for one period, seasonal differences are done over a span of S periods.

Consistent differencing: $\nabla y_t = y_t - y_{t-1}$ …………………………………..……...….. (8)

Periodic Differencing: $\nabla y_{Lt} = y_t - y_{t-L}$ ……………………………………..…………. (9)

In order to indicate the model, the number of seasonal differences- D and regular differences- d are required. While the seasonal part has its own autoregressive and moving average parameters: order P and Q, the non-seasonal part has order p and q.

Note: Seasonal parameters are the uppercase version of non-seasonal parameters. Combining the seasonal and non-seasonal terms into a single model makes way for seasonal models that have non-seasonal terms. The terms can then be added using an additive or a multiplicative form of model by applying the non-seasonal order (p, d, q), the seasonal orders (P, D, Q) for a given series, a multiplicative model is represented by the ARIMA (p, d, q) (P, D, Q) L model. After identifying the proper model, the diagnostic check is done, the same as for a non-seasonal model (Chatfield, C., 1989 and Box, G.E, Jenkins, G.M., and Reinsel, G.C., 1994).

2.4. Other Models

There are different kinds of time series models used in forecasting patient volume in the emergency department of a medical health center and some of them are explained briefly.

Exponential smoothing is a method of forecasting used in tracking variations in a time series, making use of the recently observed values that are used for updating parameters in the description of time series. The smoothed form of a new forecast for time $t + 1$ may be thought of as weighted average of the old forecast for time t while the new observation at time t having a weighted α is given to the recently observed value of $1 - \alpha$ given to the old forecast, assuming $0 \leq \alpha \leq 1$. Thus $\hat{y}_t = (1 - \alpha)\hat{y}_t + \alpha_{y_t}$. The exponential smoothing model for forecasting is given by ARIMA (0,1,1) model without a constant term (Box, G.E, Jenkins, G.M., and Reinsel, G.C., 1994).

Neural network is another type of forecasting method used in predicting the future. Neural networks are a class of comprehensive nonlinear models encouraged by researches done on the human mind. They are active and have exceptional learning and inductive effectiveness in data-rich settings and are suitable for gathering and forecasting problems. Neural networks gather intelligence from the process of learning, and then this intelligence provides them with the ability of auto-adaptability with retentive memory for performing specific duties. Since neural network can learn important information from an archive of historical information, so neural networks have acquired resourceful commercial applications. Particularly, some researches have revealed that neural network operate better than conventional statistic methods used in economic forecasting (D. Zhang, Q. Jiang and X. Li., 2005).

The Multicyclic Hubbert analysis in the production resources particularly recognizes projecting future production of petroleum resources, is now very popular in the scientific and public circles. Even though in some instances this procedure can be a very useful tool for understanding the production of resources and useful as a forecaster because at times it is exaggerated. When modeling parameters such as the number of Hubbert cycles this can significantly reduce the strength of the outcomes obtained. For example, the analysis of multicyclic Hubbert shows that it can be useful in some certain situations (Ken B. Anderson and James A. Conder., 2011).

2.5. Performance Measurement of Forecasting Methods

Performance Measures allows for the assessment of the accuracy of numerous forecasting methods applied to various time series. Performance Measures are all based on variations of predicted values from the present values in the time series: $\Delta t = yt - Ft$

2.5.1. Mean Absolute Percentage Error (MAPE)

It is also known as the Mean Absolute Percentage Deviation (MAPD). The accuracy of forecasting method in statistics are measured using MAPE for example assessment of trend analysis. It is the most commonly used measure for forecasting error and it performs best when there are no missing data. Then, multiplying the final result by 100%. MAPE is most convenient to use when there are large actual values.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{|Y_t|} \quad (10)$$

A lot of establishments pay more attention on MAPE during the evaluation of forecast accuracy. Some people prefer to work in percentage terms because it is easy for them to interpret MAPE while working with percentages. It gives clearer information for when the item’s capacity of demand is unknown. MAPE can be best used in case of high-volume data (Eric Stellwagen., 2017).

2.5.2. Mean Absolute Deviation (MAD)

It is the length form of each data value to the mean. It is used for describing variation in a set of data and helps us to understand how ‘spread out’ the values in a set of data. It is an identical unit to the original series and also equip the size of the mean no matter the significance.

$$MAD = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \quad (11)$$

MAD is a substitute for mean absolute percentage error, and it is better suited for data that are not large. As previously stated, it is impossible to calculate the percentage errors if the value is equals 0 and can easily take on big values when dealing with data that is low in volume. Such problems develop into exaggeration when averaging mean absolute percentage errors by various time series. MAD attempts to conquer such difficulty by dividing the Mean with the mean absolute deviation, basically reproportioning the error so as to make it similar across fluctuating scales of time series (Eric Stellwagen., 2017).

2.5.3. Mean Squared Deviation (MSD)

It is also known as Mean Squared Error (MSE) and shows the closeness a regression line can be to a fixed point. These distances between the points and the regression line are the "errors". Squaring is necessary to eliminate any contradictory signs. More weight is given to bigger variances. It is known as mean squared error because we are finding the average of set of errors.

$$MSD = \frac{1}{n}\sum_{t-1}^{n}(Y_t - \hat{Y}_t)^2 \quad (12)$$

MSD is used to measure the alignment of the line to the data points. For each data point, we consider the vertical distance from the point to the equivalent value of y in the error, and equate the value. Then add up values for all the data points, but in the case the value is linear we divide by the number of points and substract two. Equating is necessary for negative values to not cancel positive values. The lesser the MSE, the more it aligns with the data (Vernier., 2001).

2.5.4. Root Mean Squared Deviation (RMSD)

It normally helps in measuring the variations between values such as sample survey and population values forecasted using model and the values that were really analyzed (Wikipedia).

$$RMSD = \sqrt{\frac{1}{n}\sum_{t-1}^{n}(Y_t - \hat{Y}_t)^2} \quad (13)$$

It is the square root of MSD and it is maybe the most easily deduced statistic, since it possesses similar units as the one constructed on the y axis (Vernier., 2001).

Finally, to an inexperienced intellectual, to simply put, forecasting is inputting data into a data processing machine and leave it to do the rest of the work, but it does not work that way. The data has to be thoroughly analyzed before we can understand the development of the model. The processing machine is basically an apparatus to make forecasting much more faster for the forecaster i.e. to make the forecaster work ahead of schedule. Methods used to evaluate time series rely on the goals that requires fulfilling and the data's characteristics (Chatfield, C., 1989 and Box, G.E, Jenkins, G.M., and Reinsel, G.C., 1994).

Most of the research that has been carried out has been mainly on hospital ED in the developed world and most are about crowding and overcrowding etc. Also, most of these researchers have been using data from different hospitals ED at a time but like I said earlier that our research would be one of its kind. We will be making use of data from one particular FMC in one of the 36 states in Nigeria, Kogi state, Lokoja popularly known as the Confluence state. Also, we will be making use of the time series methods and comparing them to discover the one that most suit our models or provides the best forecast.

3. CHAPTER EMPIRICAL STUDY

3.1. Brief History of Lokoja, Kogi State, Nigeria.

Lokoja, one of the thirty-six states in Nigeria. It lies where the two rivers Niger and Benue meets each other, Lokoja city was founded in the 18th century by the British voyager known as William Baikie where an early distinctive farm was built during the unsuccessful expedition in the Niger. This city was the capital of the British Northern Nigeria Protectorate and continued to remain quite a comfortable directorial city for the foreign British administration, after the merger of Northern and Southern Nigeria in the 19th century. The first Governor-General, Sir Frederick Lugard, ruled over the new nation of Nigeria from Lokoja. The estimated inhabitants of the city then were about 90,000. The city is rich in agricultural produce because the region is closer to the rivers Niger and Benue and also shares border with federal capital territory Abuja. Beside the city of Lokoja is Ajaokuta where iron ores are usually mined for production of irons. The Local Government Area and the capital of Kogi state is Lokoja with an area of approximately 3,180km^2 and a population of about 195,261.

3.2. Data

The nature of any research work is determined by the extent of its adopted methodology. For this research, secondary data were collected and analysed through data analysis and the outcome recommendation will be based on the results of the findings.

This chapter looks at the initial analysis of PV data collected from the ED of the hospital (FMC). We chose this hospital due to the fact that it was the only hospital willing to release some few information about her patients out of many hospitals we applied to. And more importantly, it must be noted that the time frame that are being modelled was only to forecast for short-term periods.

As was mentioned earlier, monthly data were collected from FMC, which was carefully approved by the ethical committee, we were also provided with the data sheet containing the total number of monthly PV for the period of 5-year, from 1 January, 2012 to 31 December, 2016 as our training data. And also for the performance accuracy measurement, additional data was provided to us as requested for a 7-month period, from 1 January to 31 July 2017, of this present year as our test data. The table below shows the original data set collected from the hospital.

Obviously, we will notice there are some missing data from our data set from November to December of 2014 up to January of 2015. Those are the months where there were no patient arrivals at the hospital mainly due to the strike action in the country.

Table 3.1: Patient volume data set collected from FMC.

Mnoths	Year	PV	Year	PV	Year	PV	Year	PV	Year	PV
January	2012	81	2013	51	2014	41	2015	0	2016	45
February	2012	75	2013	38	2014	45	2015	42	2016	57
March	2012	41	2013	34	2014	37	2015	48	2016	30
April	2012	28	2013	26	2014	27	2015	42	2016	61
May	2012	23	2013	24	2014	28	2015	37	2016	60
June	2012	30	2013	25	2014	34	2015	45	2016	63
July	2012	32	2013	30	2014	42	2015	49	2016	59
August	2012	29	2013	39	2014	37	2015	47	2016	41
Septembe	2012	22	2013	33	2014	34	2015	52	2016	57
October	2012	30	2013	35	2014	35	2015	51	2016	64
Novembe	2012	30	2013	28	2014	0	2015	47	2016	58
December	2102	47	2013	55	2014	0	2015	70	2016	76

The table 3.2 below shows the data of patient volume collected from the hospital after properly modifying our data to fill in the gap caused by the strike action in the country between late 2014 and early 2015.

As was previously mentioned that the end of the year 2014 and early 2015 witnessed a rare strike action in the country, which led to a temporary drop in the hospital's patient visits. In this case, a highly abnormal data was experienced leaving a hole in our data to fill up. Thus, we pre-processed our data to transform the missing months of the strike action into a format that was more easily and effectively processed to our main purpose and we also modified these values properly (we assumed those are the missing values, and tried to assign values by using our statistical package). We noticed that the consequence of the strike action seems to be local. It appears to be just during the months of the strike having no lasting impediment as the consistent outline of regular differences did not stop changing following these strike months, though slowly increasing as time goes on. For the purpose of modelling the time series for future prediction, for its own usefulness, the missing months data from the strike months will better be substituted with the data that would have been probable if not for the strike situations.

Table 3.2: Modified patient volume data set collected from FMC.

Mnoths	Year	PV	Year	PV	Year	PV	Year	PV	Year	PV
January	2012	81	2013	51	2014	41	2015	42	2016	45
February	2012	75	2013	38	2014	45	2015	42	2016	57
March	2012	41	2013	34	2014	37	2015	48	2016	30
April	2012	28	2013	26	2014	27	2015	42	2016	61
May	2012	23	2013	24	2014	28	2015	37	2016	60
June	2012	30	2013	25	2014	34	2015	45	2016	63
July	2012	32	2013	30	2014	42	2015	49	2016	59
August	2012	29	2013	39	2014	37	2015	47	2016	41
Septembe	2012	22	2013	33	2014	34	2015	52	2016	57
October	2012	30	2013	35	2014	35	2015	51	2016	64
Novembe	2012	30	2013	28	2014	53	2015	47	2016	58
December	2102	47	2013	55	2014	58	2015	70	2016	76

FMC is a public hospital owned and run by the federal government of Nigeria, it includes entry facilities for solitary meetings and for short-term admission. Precautionary aid is provided due to speculation, but these are done by special groups of medical practitioners (pre-birth, nursery school children, and adult medical wards) which offer healing, precautionary and productive amenities. The stage at which technology is now in Nigeria, is not an advance stage, so electronical health record system is not in use. Thus, after having a long hour interview with the hospital managers, we were made to understand that manual recording (pen and paper recording) are used to record patient arrivals into the hospital and in fact by personally and carefully observing the personnel, it was discovered that these recordings are regularly and carefully taken and then transferred into computer systems by the personnel. Even though, they do take these recordings but manually, it does take a lot of these personnel's time and therefore decreases their performances or efficiencies in the discharge of their original duties.

3.3. Preliminary Data Analysis

In this chapter we will give the main descriptive analysis of our data.

In our dataset, we observed some several deviations which could be clearly seen in the figures below (see figure 3.1a&b). Through examining the time series carefully and as clearly noticed in the tables above, we can assume there is a positive trend in our dataset. Furthermore, the tables above show high rate of PV at the hospital in the first, second and last months of each year i.e. Januarys, Februarys and Decembers of each year experiences higher rate of patient arrivals meaning those are the busiest months for FMC personnel. Thus, obviously as seen in the tables above the recurrences of our data yearly, brings us to the conclusion that our data is seasonally inclined.

Figure 3.1 (a) shows a plot with the normal time series with a steep slope in the 36th month due to the strike action (before modifying our data) while figure 3.1 (b) show the data values with the replacement pre-processed dataset. This modified time series formulates the foundation for all additional study.

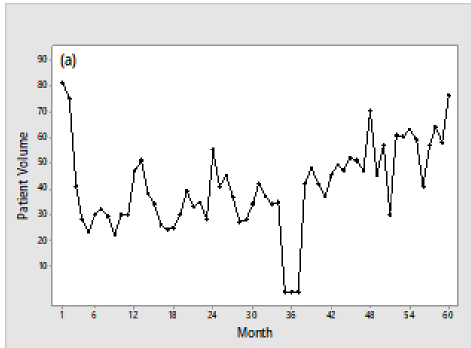

Figure 3.1a: TSA plot for monthly patient volume.

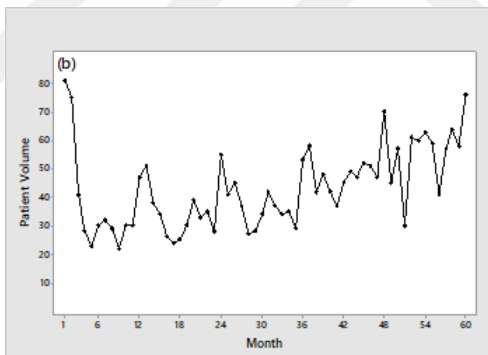

Figure 3.1b: TSA plot for monthly patient volume (after adjustment).

The above adjusted time series shows the peaks and valleys as it might have looked originally if the 3-month strike action had not occurred in the country. In further inclusion to the imminent prediction, this thesis ought to be beneficial in assembling data or developmental trends in the patient volume and on the pattern of seasonality differences, determined by the socioeconomic influences disturbing the populace and the form of ailment in that province, besides, apart from the strike action, the pattern of disease in the region could also affect the patient arrival at the hospital. There are some possible natural phenomena that influence the PV to increase or decrease per month such as the climate of the city which is a continental type characterized by adequate rainfall, high humidity (about 80% and 65% respectively in wet season and harmattan period) and high temperature (daily average is 29.6℃), the rainy season is from April to October and reaches its peak in September with an average rainfall of about 100mm.

The figure 3.2 below shows the time series plot of patient arrivals at FMC for each year from January 2012 to December 2016 making use of the overall PV and obviously the figure also shows the positive trend and seasonality of our data. The figure below also shows that the year 2016 experienced the highest patient arrivals at the hospital than the rest of the previous year, making it the busiest year for the hospital probably because of the 3-month strike action.

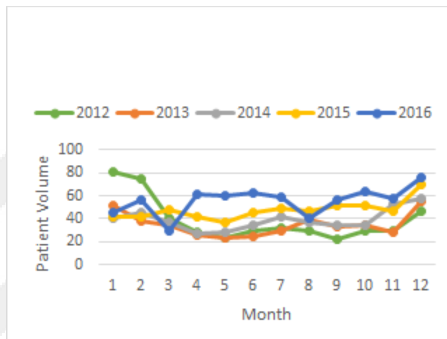

Figure 3.2: Time series plot for monthly patient volume.

Previously, we mentioned the population of Nigeria and the percentages of male and female population and we see that male population percentage was higher than the population percentage of female. The figures below show the yearly PV at the hospital for each year from 2012-2016.

The figures 3.3a-e below shows the monthly male and female patients arriving at the hospital for the whole 5-year data collected from FMC (2012-2016). They also show clearly that male patient arrivals are higher than the female patient arrivals at the hospital.

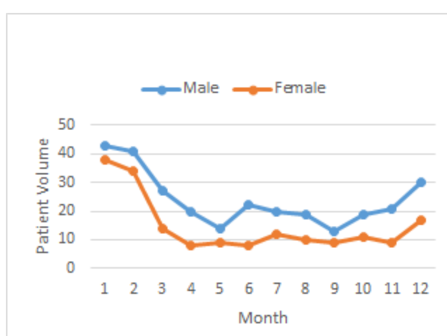

Figure 3.3a: Monthly patient volume for male/female (2012).

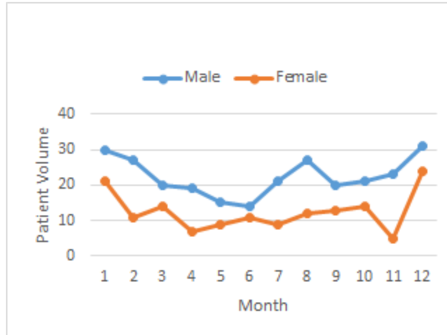

Figure 3.3b: Monthly patient volume for male/female (2013).

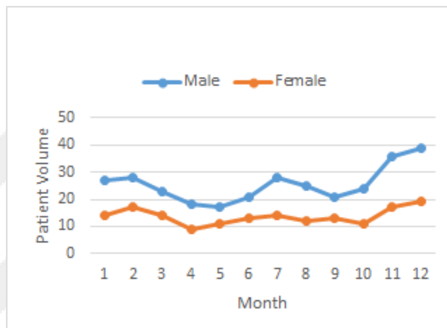

Figure 3.3c: Monthly patient volume for male/female (2014).

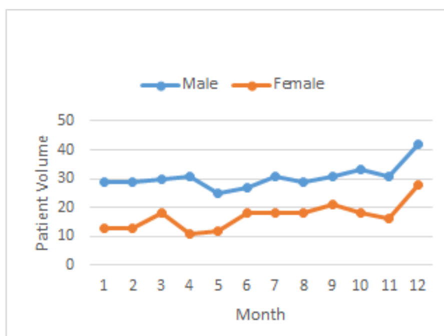

Figure 3.3d: Monthly patient volume for male/female (2015).

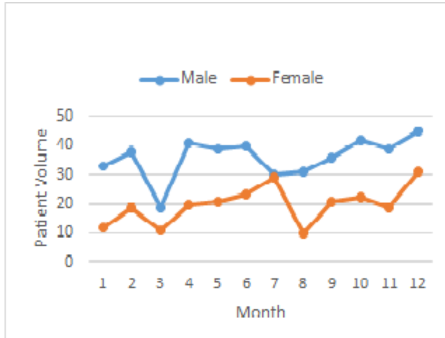

Figure 3.3e: Monthly patient volume for male/female (2016).

The table below shows the percentages of male and female patient that arrived at the hospital (FMC) on a monthly basis.

Table 3.3: Male/female percentage monthly (60) data set

Months	Years	Male	Female	PV	Male %	Female %
Jan	2012	43	38	81	53.09	46.91
Feb	2012	41	34	75	54.67	45.33
Mar	2012	27	14	41	65.85	34.14
Apr	2012	20	8	28	71.43	28.57
May	2012	14	9	23	60.87	39.13
Jun	2012	22	8	30	73.33	26.67
Jul	2012	20	12	32	62.5	37.5
Aug	2012	25	10	29	86.21	34.48
Sep	2012	13	12	22	59.09	54.55
Oct	2012	19	11	30	63.33	36.67
Nov	2012	21	9	30	70	30
Dec	2012	30	17	47	63.83	36.17
Jan	2013	30	21	51	58.82	41.18
Feb	2013	27	11	38	71.05	28.95
Mar	2013	20	14	34	58.82	41.18
Apr	2013	19	7	26	73.08	26.92
May	2013	15	9	24	6.25	37.5
Jun	2013	14	11	25	56	44
Jul	2013	21	13	30	70	43.33
Aug	2013	27	12	39	69.23	30.77
Sep	2013	20	13	33	60.61	39.39
Oct	2013	21	14	35	60	40
Nov	2013	23	5	28	82.14	17.86
Dec	2013	31	24	55	56.36	43.64
Jan	2014	27	14	41	65.85	34.15
Feb	2014	28	17	45	62.22	37.78
Mar	2014	23	14	37	62.16	37.84
Apr	2014	18	9	27	66.67	33.33
May	2014	17	11	28	60.71	39.29
Jun	2014	21	13	34	61.76	38.24
Jul	2014	28	14	42	66.67	33.33
Aug	2014	25	12	37	67.57	32.43
Sep	2014	21	13	34	61.76	38.24
Oct	2014	24	11	35	68.57	31.43
Nov	2014	36	17	53	67.92	32.08
Dec	2014	39	19	58	67.23	32.76
Jan	2015	29	13	42	69.04	30.95
Feb	2015	29	13	42	69.04	30.95
Mar	2015	30	18	48	62.5	37.5
Apr	2015	31	11	42	73.81	26.19
May	2015	25	12	37	67.57	32.43
Jun	2015	27	18	45	60	40
Jul	2015	31	18	49	63.27	36.73
Aug	2015	29	18	47	61.7	38.2
Sep	2015	31	21	52	59.62	40.38
Oct	2015	33	18	51	64.71	35.29
Nov	2015	31	16	47	65.96	34.04
Dec	2015	42	28	70	60	40
Jan	2016	33	12	45	73.33	26.67
Feb	2016	38	19	57	66.67	33.33
Mar	2016	19	11	30	63.33	36.67
Apr	2016	41	20	61	67.21	32.79
May	2016	43	21	60	71.67	35
Jun	2016	40	25	63	63.49	39.68
Jul	2016	30	29	59	50.85	49.15
Aug	2016	31	10	41	75.61	24.39
Sep	2016	36	21	57	63.16	36.84
Oct	2016	42	22	64	65.63	34.38
Nov	2016	39	19	58	67.24	32.76
Dec	2016	45	31	76	59.21	40.79
				Avg=	64.17116667	35.8475
					64.17	35.85
				Total=		100

Furthermore, we decide to generate the average number of male and female patients visiting the hospital (FMC) on a monthly basis, which will be used for direct and indirect forecasting in chapter 4 of sub-section 4.4.1. (direct forecasting) and 4.4.2. (indirect forecasting) respectively.

In order to be more confident about the stationarity test of our data analysis, we applied a stationarity test to make accurate conclusions. Consequently, the Augment Dickey-Fuller test was used to check for the stationarity of the monthly patient volume data as shown in the table below:

The table 3.4. below shows the summary of the test result for the stationarity of our dataset.

Table 3.4: Data stationarity

Null Hypothesis: PV has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.285616	0.0201
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PV)
Method: Least Squares
Date: 08/09/17 Time: 11:14
Sample (adjusted): 3 60
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PV(-1)	-0.401255	0.122125	-3.285616	0.0018
D(PV(-1))	-0.128498	0.130651	-0.983515	0.3297
C	16.77749	5.334917	3.144846	0.0027

R-squared	0.236143	Mean dependent var	0.017241
Adjusted R-squared	0.208366	S.D. dependent var	12.31102
S.E. of regression	10.95358	Akaike info criterion	7.675548
Sum squared resid	6598.951	Schwarz criterion	7.782123
Log likelihood	-219.5909	Hannan-Quinn criter.	7.717061
F-statistic	8.501483	Durbin-Watson stat	1.724070
Prob(F-statistic)	0.000607		

Therefore, since $p < 0.05$, we cast-off the null hypothesis of the PV as a unit root which destroys stationarity of the data. Thus, we conclude that PV is stationary as was mentioned earlier and by so doing, integration was not a necessary thing to do while applying ARIMA $(p, d, q) \times (P, D, Q)$. The result of the test is summarized in the table above.

3.4. Autocorrelation and Partial Autocorrelation Functions (ACF & PACF)

In generating forecast for our data set, since ARIMA method will be used, ACF and PACF are important models that helps in forecasting into the future.

The ACF model of lag k is estimated for the $(n-k)$ sets and is shown in the equation below which is also the method for estimating the lag k autocorrelation coefficient (r_k) between the comparisons of Y_t and Y_{t-k} separated by k periods.

$$r_k = \frac{\sum_{t=k+1}^{\cap}(Y_t-\bar{Y})(Y_{t-k}-\bar{Y})}{\sum_{t-1}^{\cap}(Y_t-\bar{Y})^2} \quad (14)$$

k= 0, 1, 2

Where:

r_k= observation coefficient for lag of k periods

$\bar{Y}$= mean of values of each series

Y_t= observation in period t

Y_{t-k}= observation k period earlier or at period $t-k$

The measure of the relationship observed between the linear and time series models is disconnected by the lag of k units period. The order p of such model is appropriately analyzed using the autocorrelation coefficient. While the PACF of lag k is expressed by ϕ_{kk}, and measures the relationship between Y_t and Y_{t-k} after modification of $Y_{t-1}, Y_{t-2}, \dots, Y_{t-k+1}$. The modification of Y_t and Y_{t-k} to test the kind of correlation Y_t has with $Y_{t-1}, Y_{t-2}, \dots, Y_{t-k+1}$.

The table 3.5 below shows the summary of the characteristics of ACF and PACF for AR, MA, and ARMA models. It is noted that the performance of the ACF and PACF are contradictory to that of AR and MA models.

Table 3.5: Summary of the characteristics of ACF and PACF for AR, MA and ARMA models (Shakira Green, 2011).

	AR (p)	MA (q)	ARMA (p, q)
ACF	Dies out	Cuts off after lag q	Dies out
PACF	Cuts off after lag p	Dies off	Dies out

The ACF is a tool used to find patterns in the data. Indicatively, the autocorrelation function shows us the correlation between points disconnected by various time lags. In time series we will notice that PACF gives an incomplete link of time series at all short lags, and it contradicts the ACF, which controls all the other lags. In identifying the autoregressive (AR) model it is regularly done using PACF while in identifying the moving average (MA) model is frequently done using ACF rather than PACF.

Additionally, there are different kinds of Box-Jenkins models which are well-known by the amount of their autoregressive parameters (p), the degree of differencing (d) and the moving average parameters (q), and somewhat this model may well be written by means of the constant symbolism of the autoregressive integrated moving average (ARIMA) (p, d, q). Therefore, to probe the appropriate type of model, we begin first by observing the autocorrelation and partial autocorrelation functions.

ARIMA method will be used in forecasting the PV, and while defining these methods ACF and PACF are important functions. Thus, in this section, we are going to generate those functions in accordance with our data. ACF plots shown in the figurative illustration of the autocorrelation construction of time series variables. The ACF plots can be used in determining to which level degree historical values of a given time series are correlated to imminent values of the same time series variables. Even more so, it provides understanding on the reliability of the historical values which are for forecasting future values. PACF plots on the other hand shows the illustration in representation of the partial autocorrelation structure of the time series variable. PACF is essentially the autocorrelation of an indication with itself at distinctive periods in time, with linear reliance with that indication detaching at shorter lags, making the lag function in between different period of time. The figure 3.4 (a & b) below shows the plots of ED patient volume of FMC, the ACF cuts-off immediately after the next lag abruptly while the PACF dies-out to zero exponentially. Although, according to the ACF and PACF plots below, we observe stationarity in our data set.

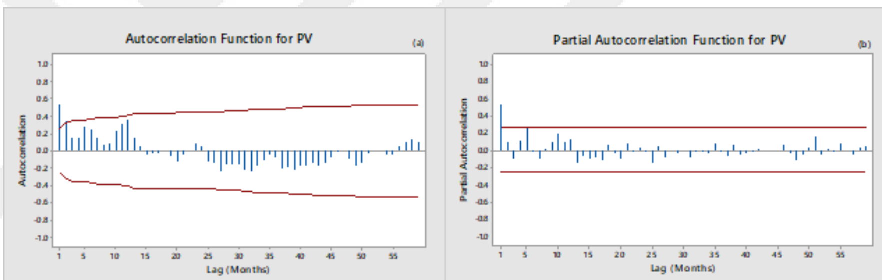

Figure 3.4: ACF and PACF for patient volume of FMC.

4. CHAPTER RESULTS

In this chapter, we look at the results from the different types of methods we employed in our research work and use these results appropriately. The different time series methods that were applied in predicting PV in the hospital settings and the first one we used which was the Winters' method and the model result is discussed below.

4.1. Winters' Method

Winters' method which could also be regarded as triple exponential smoothing method, is a method that uses three smoothing constants and it is a method for projecting the future provided that the series is ''seasonal'' i.e. repetitive over some period. In determining the optimum of the smoothing constant of our model parameters, we used trial and error methods. After repeating more than 100trials, we get the best smoothing constant with minimum MAPE for our model using the 60-months training data collected from FMC without using the new 7-months test data for the year 2017 as was previously explained.

The figure 4.1 below shows the graph representation for the Winters' method and it shows the smoothing constants of the α (alpha) which is 0.3802, γ (gamma) with 0.2031 and the δ (beta) with 0.1000 and these smoothing constants were the best we could manage to get. Furthermore, the figure also shows the MAPE which was 16.18%, MAD was 6.85% and the MSD was 87.50%, making use of the Winters' multiplicative method.

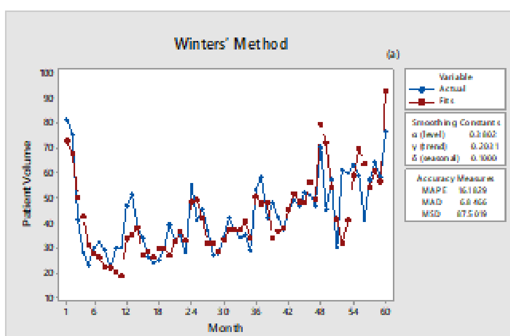

Figure 4.1: Winters' multiplicative method for 60-months data set.

4.2. ARIMA Models

In this section we will be looking into all the details and properties of applying ARIMA models which was the second method we used in forecasting the PV in the hospital (FMC).

4.2.1. Model Building Strategy Implementation

The process of model building strategy is as follows:

Identifying the model	Model evaluation	Model survey	Model prediction

Step 1: Model identification: This is used for determining whether or not the series is fixed i.e. the time series seems to differ on a static level. A time series that is nonstationary indicates that the series seems to increase or decrease as time goes on allowing the autocorrelation to pass out swiftly. Models for a nonstationary series are known as the autoregressive integrated moving average models denoted by ARIMA (p, d, q)

p-order of autoregressive

d-amount of differencing

q-order of moving average

Once we have obtained the stationary series, the procedure of the model to be used is then identified. Each and every ARIMA model has an exceptional set of autocorrelation and partial autocorrelation and the hypothetical patterns are then matched with the equivalent values.

Step 2: Model evaluation: The variables in our ARIMA models were evaluated by diminishing the summation of squares of the appropriate flaws, the remaining mean square error is the estimation of the dissimilarities of the particular error ε_t evaluated. This mean square errors are suitable for evaluating appropriate models and also used to analyse the error limits of forecasts.

Step 3: Model checking: Before we can use our model for future prediction, we have to lookout for the competence of our model by surveying it and essentially a model can be acceptable if the leftover models cannot be used for the progression of our forecasts i.e. we should randomize the remaining models. An unused autocorrelation ought to be of no importance and commonly with in this equation $\pm 2/\sqrt{n}$ of 0. Substantial residuals at short lags or recurrent lags propose that if such model is insufficient then we can select a newly modified model.

Step 4: Model forecasting: After the selection of an adequate model is complete, the more data is available at our disposal guarantees us with generating forecast into the future by using the same ARIMA model. As long as we have new dataset

4.2.2. Proper Models for Forecasting Patient Volume

Different models with varying values of (p, q) and (P, Q) were applied as was previously mentioned in section 3 of our study. The fact that our data was stationary, it was not necessary to differentiate our data. Thus, $d = D = 0$ in our analysis.

This section summarises the results of just the proper models. For us to be sure that our models are proper, we give the respective ACF and PACF figures of our data after the application of differencing the models. The ACF and PACF figures which have ignorable correlations (correlations in the lags within the error limit) are observed as proper methods.

4.2.2.1. ARIMA $(\mathbf{1}, \mathbf{0}, \mathbf{0})$

This was the first model we applied, ARIMA $(1,0,0)$. The summary result of this model is represented in table 4.1 below.

Table 4.1: Results of ARIMA $(1,0,0)$

Final Estimates of Parameters

Type	Coef.	SE Coef.	T	P
AR 1	0.70	0.10	6.61	0.000
Constant	14.33	1.48	9.71	0.000
Mean	45.51	4.69		

Number of observations: 60

Residuals: SS = 7340.70 (back forecasts excluded)

MS = 126.56 DF = 58

According to table 4.1 values, we observed that both the AR (1) and the constant values are statistically significant since $p < 0.05$. Based on these observations, the model equation can be written as follows:

$$\hat{Y}_t = 14.33 + 0.70Y_{t-1}$$

After applying the ARIMA (1,0,0) model to our data set correctly, the ACF and PACF figures of residuals cab be represented in figure 4.2a&b below.

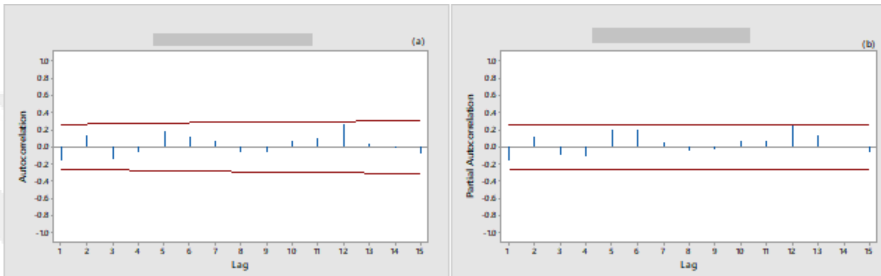

Figure 4.2(a, b): ACF & PACF residuals for ARIMA (1,0,0)

According to the figure 4.2 values, we concluded that ARIMA (1,0,0) model is proper for our data set, since the correlations in this figure are all within the error limits.

4.2.2.2. ARIMA (2,0,0)

The summary of the result for ARIMA (2,0,0) is shown in the table 4.2 below.

Table 4.2: Results of ARIMA (2,0,0)

Final Estimates of Parameters				
Type	Coef.	SE Coef.	T	P
AR 1	0.60	0.14	4.41	0.000
AR 2	0.17	0.13	1.30	0.200
Constant	10.81	1.52	7.13	0.000
Mean	47.12	6.61		
Number of observations: 60				
Residuals: SS = 7178.58 (back forecasts excluded)				
MS = 125.94		DF = 57		

From table 4.2 values above, we observed that the AR (1) and the constant values are the only statistically significant to our model i.e. $p < 0.05$. While the AR (2) value is statistically insignificant to our model i.e. $p > 0.05$. Our model equation is given as follows:

$$\hat{Y}_t = 10.81 + 0.60Y_{t-1} + 0,17Y_{t-2}$$

After applying ARIMA (2,0,0) model to our data set properly, the ACF and PACF figures of the residuals are given in figure 4.3 below:

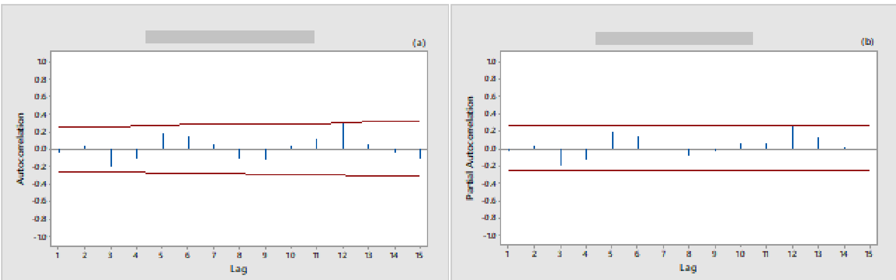

Figure 4.3(a, b): ACF & PACF residuals for ARIMA (2,0,0)

According to figure 4.3 values, we came to the conclusion that ARIMA (2,0,0) model is a proper method for our data set, although, AR (2) is statistically insignificant to our model, we can still assume the model to be a proper model because the correlations are well within their control limit. We can see that lag12 of the 12month is actually higher, signifying a seasonality in our data set.

Furthermore, we applied ARIMA (3,0,0) model but we observed that after this point, the model parameters begin to be statistically insignificant, namely the p −value of MA (3), MA (4), MA (5) are all greater than the $p < 0.05$. Thus, we did not need to summarize the results of these residuals.

4.2.2.3. ARIMA $(\mathbf{1},\mathbf{0},\mathbf{0}) \times (\mathbf{1},\mathbf{0},\mathbf{0})_{\mathbf{12}}$

Summary of the result of this model is presented below in table 4.3:

Table 4.3: Results of ARIMA $(1,0,0) \times (1,0,0)_{12}$

Final Estimates of Parameters

Type	Coef	SE Coef	T	P
AR 1	0.49	0.12	4.05	0.000
SAR 12	0.89	0.12	7.41	0.000
Constant	2.65	1.41	1.88	0.065
Mean	48.85	25.98		

Number of observations: 60

Residuals: SS = 5676.31 (back forecasts excluded)

MS = 99.58 DF = 57

We observe from the values of the bale 4.3 above that AR (1) and SAR (12) values are both statistically significant i.e. $p < 0.05$, while the constant value is statistically insignificant i.e. $p > 0.05$. Though, this does not really matter, since our model equation is given as follows:

$$\hat{Y}_t = 2.65 + 0.49Y_{t-1} + 0.89Y_{t-12}$$

After applying our model to the data set properly, we give the ACF and PACF figures of the residuals are given below:

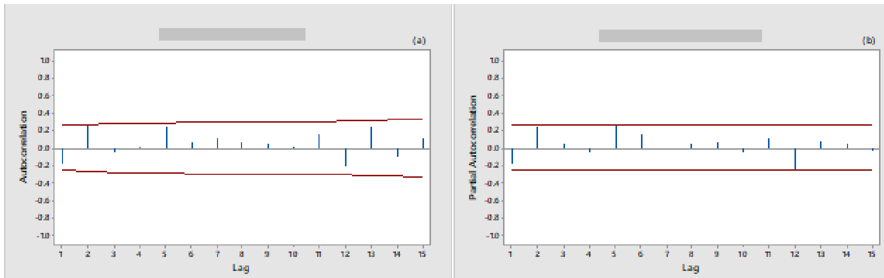

Figure 4.4(a, b): ACF & PACF for ARIMA $(1,0,0) \times (1,0,0)_{12}$

According to figure 4.4 values above, we conclude that the model is proper for our data set as we can clearly see that the correlations are within their error limits. Also, the figure depicts the seasonality in our data clearly from lags (2,5 and 12).

4.2.2.4. ARIMA $(\mathbf{1,0,0}) \times (\mathbf{2,0,0})_{\mathbf{12}}$

We applied the model above and summary output of the result of this model is represented in table 4.4 below:

Table 4.4: Results of ARIMA $(1,0,0) \times (2,0,0)_{12}$

Final Estimates of Parameters

Type	Coef	SE Coef	T	P
AR 1	0.87	0.07	12.66	0.000
SAR 12	0.00	0.13	0.01	0.993
SAR 24	0.96	0.13	7.64	0.000
Constant	0.30	1.19	0.25	0.803
Mean	66.2	264.1		

Number of observations: 60

Residuals: SS = 4206.91 (back forecasts excluded)

MS = 75.12 DF = 56

According to the table above, we can observe that the AR (1) and SAR (24) values are statistically significantly i.e. $p < 0.05$. While SAR (12) and the constant values are statistically insignificant i.e. $p > 0.05$ and based on this observation we can write the equation as follows:

$\hat{Y}_t = 0.30 + 0.87Y_{t-1} + 0.96Y_{t-24}$

After applying ARIMA $(1,0,0) \times (2,0,0)_{12}$ model to the data properly, ACF and PACF figures of the residuals can now be represented in the figure below:

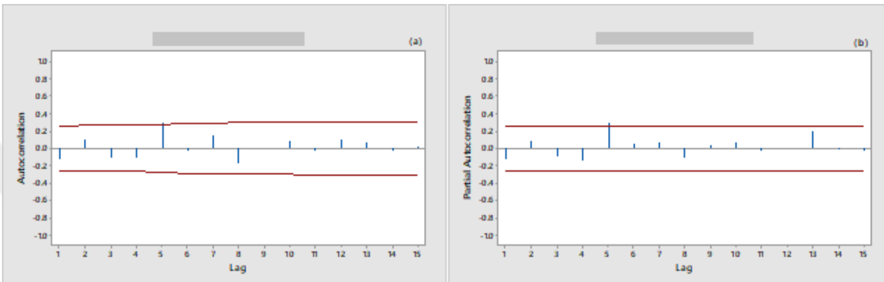

Figure 4.5(a, b): ACF & PACF residuals for ARIMA $(1, 0, 0) \times (2, 0, 0)_{12}$

According to figure 4.5 values above, we conclude that ARIMA $(1,0,0) \times (2,0,0)_{12}$ model for figure 4.5a is a proper model for our data set because the correlations are within the control limit but as for figure 4.5b, we can say it is not a proper model for our data set due to the fact that lag5 is above the error limit.

4.2.2.5. ARIMA $(\mathbf{1},\mathbf{0},\mathbf{0}) \times (\mathbf{0},\mathbf{0},\mathbf{1})_{\mathbf{12}}$

The model above was applied and the summary output of the model is given in the table below:

Table 4.5: Results of ARIMA $(1,0,0) \times (0,0,1)_{12}$

Final Estimates of Parameters

Type	Coef	SE Coef	T	P
AR 1	0.5585	0.1171	4.77	0.000
SMA 12	-0.4421	0.1674	-2.64	0.011
Constant	19.923	1.972	10.10	0.000
Mean	45.122	4.466		

Number of observations: 60

Residuals: SS = 6415.61 (back forecasts excluded)

MS = 112.55 DF = 57

According to the values of the table 4.5 above, we observe that AR (1), SMA (12) and the constant values are all statistically significant i.e. $p < 0.05$. The observation above brings us to the equation as written below:

$$\hat{Y}_t = 19.92 + 0.56Y_{t-1} + 0.44\varepsilon_{t-12}$$

After applying ARIMA $(1,0,0) \times (0,0,1)_{12}$ model to our data set properly, the ACF and PACF figures of the residuals are depicted below in figure 4.6a&b:

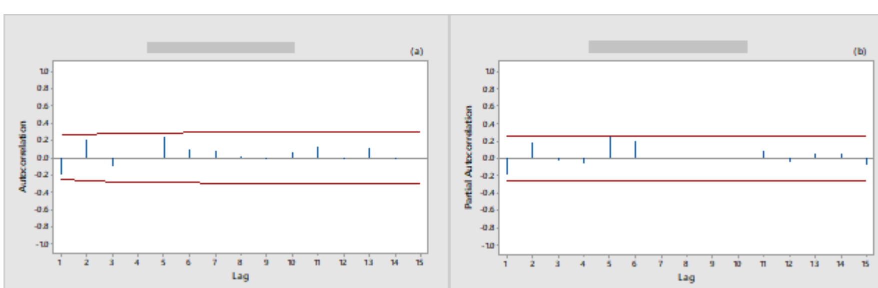

Figure 4.6(a, b): ACF & PACF residuals for ARIMA $(1,0,0) \times (0,0,1)_{12}$

From the values of figure 4.6 above, we conclude that ARIMA $(1,0,0) \times (0,0,1)_{12}$ model is proper for our data set, as it can be glaringly seen that the correlations in the figures are well within their control limits.

4.2.2.6. ARIMA $(\mathbf{1}, \mathbf{0}, \mathbf{0}) \times (\mathbf{0}, \mathbf{0}, \mathbf{2})_{\mathbf{12}}$

We also applied ARIMA $(1,0,0) \times (0,0,2)_{12}$ model and the summary output of the result of the model is given in the table below:

Table 4.6: Results of ARIMA $(1,0,0) \times (0,0,2)_{12}$

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
AR 1	0.63	0.12	5.28	0.000
SMA 12	-0.51	0.22	-2.38	0.021
SMA 24	-0.74	0.22	-3.44	0.001
Constant	17.62	2.19	8.06	0.000
Mean	47.06	5.84		
Number of observations: 60				
Residuals: SS = 3955.25 (back forecasts excluded)				
MS = 70.63		DF = 56		

According to the table 4.6 values above AR (1), SMA (12), SMA (24) and the constant values are all statistically significant i.e. $p < 0.05$ which brings us to the equation of the model as shown below:

$$\hat{Y}_t = 17.62 + 0.63Y_{t-1} + 0.51\varepsilon_{t-12} + 0.74\varepsilon_{t-24}$$

After applying ARIMA $(1,0,0) \times (0,0,2)_{12}$ to our data set, the ACF and PACF figures of the residuals are then depicted below:

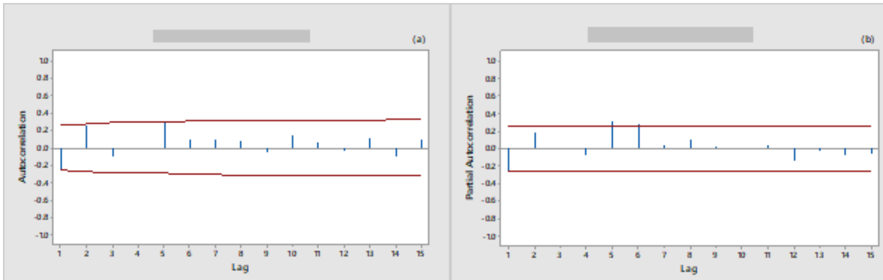

Figure 4.7(a, b): ACF & PACF residuals for ARIMA $(1,0,0) \times (0,0,2)_{12}$

According to the figure 4.7 values above, we conclude ARIMA $(1,0,0) \times (0,0,2)_{12}$ model for figure 4.7a is proper for our data set because all the correlations are within their error limits but because the correlations in the figure 4.7b are above their error limits of lags 5 and 6 are above their control limits.

After this point we observed that the model parameters begin to be statistically insignificant, therefore, we decide not to continue with the rest of the models.

4.2.2.7. ARIMA $(\mathbf{0}, \mathbf{0}, \mathbf{1})$

Table 4.7: Result of ARIMA (0,0,1)

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
MA 1	-0.44	0.12	-3.61	0.001
Constant	43.50	2.34	18.60	0.000
Mean	43.50	2.34		
Number of observations: 60				
Residuals: SS = 9198.77 (back forecasts excluded)				
MS = 158.60		DF = 58		

From the table 4.7 values above, it was observed that the constant and MA (1) values are both statistically significant and then the model equation was attained below:

$$\hat{Y}_t = 43.50 + 0.44\varepsilon_{t-1}$$

After the application of ARIMA (0,0,1) model to our data set properly, the ACF and PACF figures of the residuals are given as follows in figure 4.8a&b respectively:

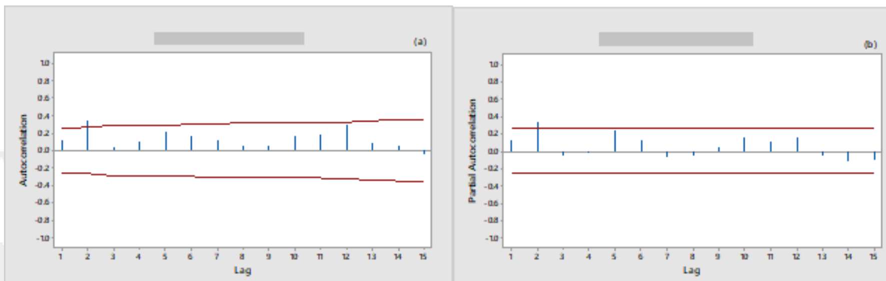

Figure 4.8(a, b): ACF & PACF residuals for ARIMA (0,0,1)

According to the values of the figures above, we conclude that ARIMA (0,0,1) model is a proper for our data set, but obviously we can see that lag1 in the figures above is above the error limits while the rest of the correlations are well within their control limits.

4.2.2.8. ARIMA $(\mathbf{0}, \mathbf{0}, \mathbf{2})$

Table 4.8: Results of ARIMA (0,0,2)

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
MA 1	-0.43	0.09	-4.65	0.000
MA 2	-0.69	0.09	-7.40	0.000
Constant	44.13	2.88	15.35	0.000
Mean	44.13	2.88		
Number of observations: 60				
Residuals: SS = 6416.34 (back forecasts excluded)				
MS = 112.57		DF = 57		

From the depicted figure above, we observe that the MA (1), MA (2) and the constant values are all statistically significant i.e. $p < 0.05$. Based these observations, the model equation can be written as follows:

$$\hat{Y}_t = 44.13 + 0.43\varepsilon_{t-1} + 0.69\varepsilon_{t-2}$$

After applying the ARIMA (0,0,2) model to our data set accordingly, the ACF and PACF figures of residuals can be represented in the figure below:

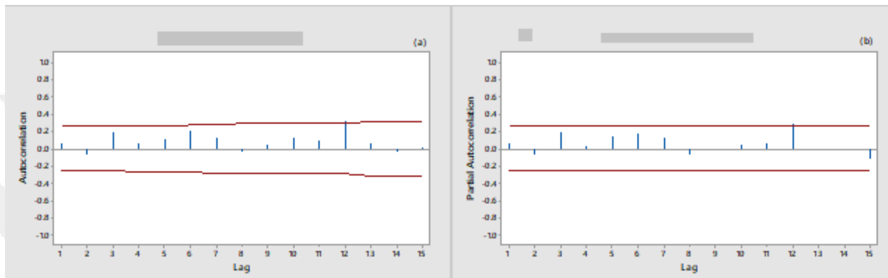

Figure 4.9(a, b): ACF & PACF residuals for ARIMA (0,0,2)

From the figure 4.9 values above, we conclude that ARIMA (0,0,2) model is proper for our data set mainly because the correlations in the figures are all within the error limits.

4.2.2.9. ARIMA $(0, 0, 3)$

Table 4.9: Results of ARIMA (0,0,3)

Final Estimates of Parameters

Type	Coef	SE Coef	T	P
MA 1	-0.65	0.13	-5.15	0.000
MA 2	-0.82	0.11	-7.68	0.000
MA 3	-0.30	0.13	-2.34	0.023
Constant	44.56	3.61	12.34	0.000
Mean	44.56	3.61		

Number of observations: 60

Residuals: SS = 5904.69 (back forecasts excluded)

MS = 105.44 DF = 56

According to the table 4.9 values above, we observed that the MA (1), MA (2), MA (3) and the constant values are all statistically significant since $p < 0.05$. Due to this observation, the equation of the model is given as follows:

$$\hat{Y}_t = 44.56 + 0.65\varepsilon_{t-1} + 0.82\varepsilon_{t-2} + 0.30\varepsilon_{t-3}$$

We properly applied ARIMA (0,0,3) model to our data set and the ACF and PACF figures of residuals are given in figure 4.9a&b below:

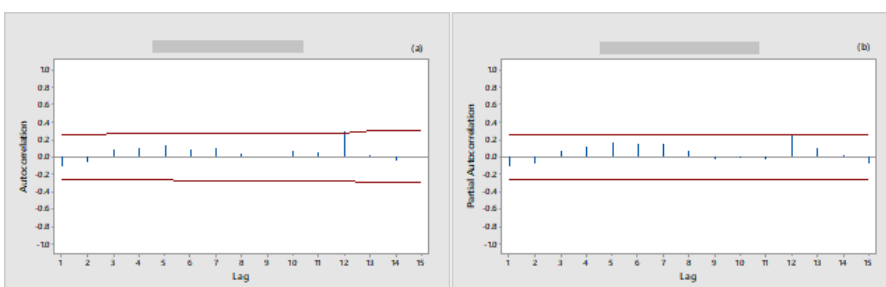

Figure 4.10(a, b): ACF & PACF residuals for ARIMA (0,0,3)

According to figure 4.10 values, it was concluded that ARIMA (0,0,3) model is quite proper for our data set, due to the fact that the correlations in the figures are all well within the control limits.

After this point, we observed that the rest of the ARIMA model parameters are beginning to be statistically insignificant i.e. $p > 0{,}05$, therefore we could not move on with the rest of the models.

4.2.2.10. ARIMA $(\mathbf{0}, \mathbf{0}, \mathbf{1}) \times (\mathbf{1}, \mathbf{0}, \mathbf{0})_{\mathbf{12}}$

Table 4.10: Results of ARIMA $(0,0,1) \times (1,0,0)_{12}$

Type	Coef	SE Coef	T	P
MA 1	-0.29	0.13	-2.28	0.027
SAR 12	0.94	0.11	8.37	0.000
Constant	2.84	2.17	1.31	0.196
Mean	51.07	39.02		

Final Estimates of Parameters

Number of observations: 60

Residuals: SS = 6360.23 (back forecasts excluded)

MS = 111.58 DF = 57

According to the values of the table 4.10 above, we can obviously see that MA (1) and SAR (12) values are statistically significant i.e. $p < 0{,}05$, while the constant is statistically insignificant i.e. $p > 0.05$. Based on the above information, the model equation is depicted as follows:

$\hat{Y}_t = 2.84 + 0.29\varepsilon_{t-1} + 0.94Y_{t-12}$

After the application of ARIMA $(0,0,1) \times (1,0,0)_{12}$ model to our data set accurately, the ACF and PACF figures of the residuals are given in figure 4.10a&b below:

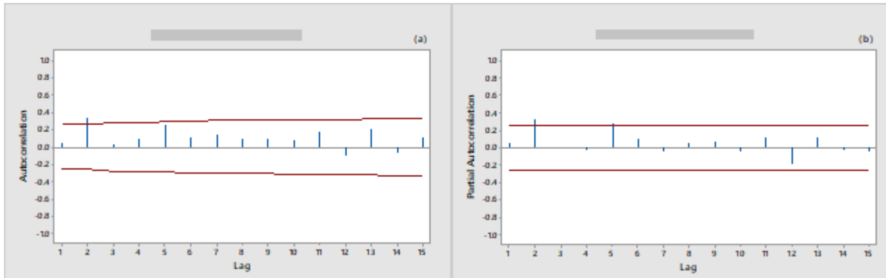

Figure 4.11(a, b): ACF & PACF residuals for ARIMA $(0,0,1) \times (1,0,0)_{12}$

From the values of figure 4.11 above, we can conclude that ARIMA $(0,0,1) \times (1,0,0)_{12}$ model is proper for our data set because most of the correlations are within the control limit. But we can see that some lags are above their error limits (lag 1 of figure 4.11a and lag 1 and 5 of figure 4.11b).

4.2.2.11. ARIMA $(\mathbf{0}, \mathbf{0}, \mathbf{1}) \times (\mathbf{2}, \mathbf{0}, \mathbf{0})_{\mathbf{12}}$

Table 4.11: Results of 4.2.2.11. ARIMA $(0,0,1) \times (2,0,0)_{12}$

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
MA 1	-0.31	0.13	-2.39	0.020
SAR 12	0.86	0.19	4.60	0.000
SAR 24	0.08	0.18	0.45	0.652
Constant	2.95	2.40	1.23	0.224
Mean	51.91	42.24		
Number of observations: 60				
Residuals: SS = 6346.03 (back forecasts excluded)				
MS = 113.32		DF = 56		

According to the values of the table above, MA (1) and SAR (12) values are statistically significant i.e. $p < 0.05$, while SAR (24) and the constant values are statistically insignificant i.e. $p > 0.05$. Based on the above information, the equation of the model can be shown below:

$$\hat{Y}_t = 2.95 + 0.31\varepsilon_{t-1} + 0.86Y_{t-12} + 0.08Y_{t-24}$$

We then apply the ARIMA $(0,0,1) \times (2,0,0)_{12}$ model to our data carefully, the ACF and PACF figures of residuals was then derived as shown in the figure below:

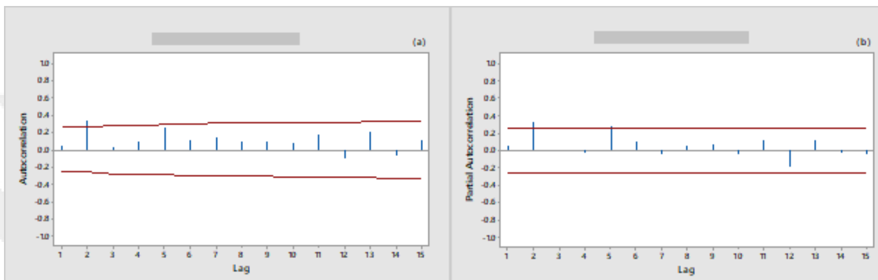

Figure 4.12(a, b): ACF & PACF residuals for ARIMA $(0,0,1) \times (2,0,0)_{12}$

From the values figure 4.12 above, we conclude that ARIMA $(0,0,1) \times (2,0,0)_{12}$ model may be proper for our model if all the correlations are well within the control limits but lags 1 of figure 4.12a&b are above the error limits.

4.2.2.12. ARIMA $(\mathbf{0}, \mathbf{0}, \mathbf{1}) \times (\mathbf{3}, \mathbf{0}, \mathbf{0})_{\mathbf{12}}$

Table 4.12: Results of ARIMA (0,0,1) × $(3,0,0)_{12}$

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
MA 1	-0.36	0.13	-2.79	0.007
SAR 12	0.84	0.12	6.99	0.000
SAR 24	0.84	0.14	5.99	0.000
SAR 36	-0.98	0.11	-9.18	0.000
Constant	22.61	3.43	6.60	0.000
Mean	76.72	11.62		
Number of observations: 60				
Residuals: SS = 3285.31 (back forecasts excluded)				
MS = 59.73		DF = 55		

According to the values of the table 4.12 above, we observed that the MA (1), SAR (12), SAR (24), SAR (36) and the constant values are all statistically significant meaning $p < 0.05$. Based on these observations, we can the write the model equation which is as follows:

$$\hat{Y}_t = 22.61 + 0.36\varepsilon_{t-1} + 0.84Y_{t-12} + 0.84Y_{t-24} + 0.98Y_{t-36}$$

After the application of ARIMA $(0,0,1) \times (3,0,0)_{12}$ model carefully to our data set, the ACF and PACF residual figures are then given as in figure 4.13a&b below:

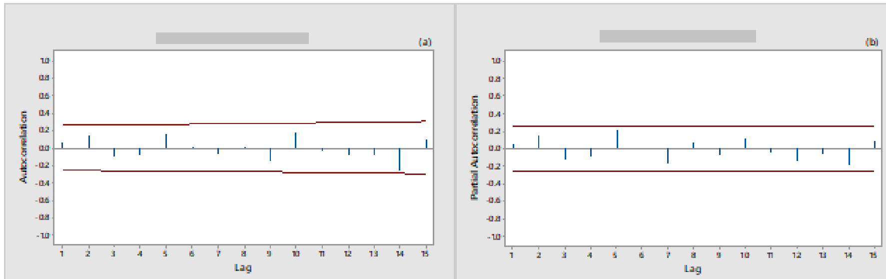

Figure 4.13(a, b): ACF & PACF residuals for ARIMA $(0,0,1) \times (3,0,0)_{12}$

According to the values of the figures above, we came to the conclusion that ARIMA $(0,0,1) \times (3,0,0)_{12}$ model is proper for our data set, since the correlations in the figures are all well within their error limits.

4.2.2.13. ARIMA. $(\mathbf{0},\mathbf{0},\mathbf{1}) \times (\mathbf{4},\mathbf{0},\mathbf{0})_{\mathbf{12}}$

Table 4.13: Results for ARIMA. $(0,0,1) \times (4,0,0)_{12}$

Final Estimates of Parameters

Type	Coef	SE Coef	T	P
MA 1	-0.19	0.13	-1.41	0.165
SAR 12	0.07	0.14	0.51	0.609
SAR 24	1.65	0.16	10.08	0.000
SAR 36	-0.10	0.01	-1.06	0.294
SAR 48	-0.90	0.12	-7.68	0.000
Constant	30.79	5.79	5.32	0.000
Mean	109.66	20.61		

Number of observations: 60

Residuals: SS = 2594.66 (back forecasts excluded)

MS = 48.05 DF = 54

From the values of the table above, we observe that MA (1), SAR (12) and SAR (36) values are statistically insignificant meaning $p > 0,05$, while the SAR (24), SAR (48) and the constant are statistically significant i.e. $p < 0.05$. Based on the information from the table above, the equation of the model can be given as follows:

$$\hat{Y}_t = 30.79 + 0.19\varepsilon_{t-1} - 0.07Y_{t-12} - 1.65Y_{t-24} + 0.10Y_{t-36} + 0.90Y_{t-48}$$

After the application of ARIMA $(0,0,1) \times (4,0,0)_{12}$ model to our data set properly, the ACF and PACF figures of residuals can be shown below:

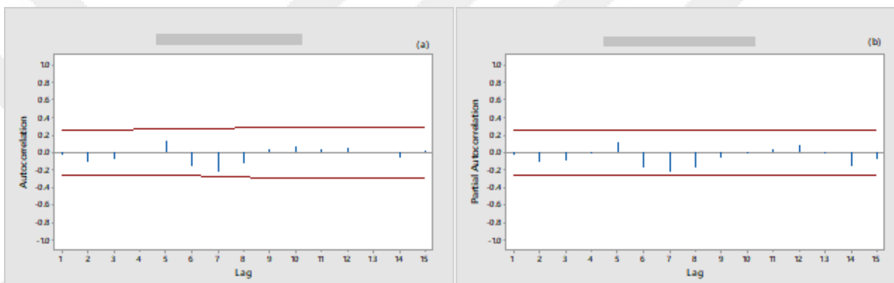

Figure 4.14(a, b): ACF & PACF residuals for ARIMA $(0,0,1) \times (4,0,0)_{12}$

According to the values of the figure above, we conclude that ARIMA $(0,0,1) \times (4,0,0)_{12}$ model is proper for our data set, since the correlations in the figures are all well within the error limits.

4.2.2.14. ARIMA $(0,0,2) \times (1,0,0)_{12}$

Table 4.14: Results of ARIMA $(0,0,2) \times (1,0,0)_{12}$

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
MA 1	-0.39	0.11	-3.51	0.001
MA 2	-0.54	0.11	-4.80	0.000
SAR 12	0.84	0.12	7.21	0.000
Constant	7.42	2.47	3.01	0.004
Mean	47.39	15.74		
Number of observations: 60				
Residuals: SS = 4859.69 (back forecasts excluded)				
MS = 86.78		DF = 56		

From the values of the table above, it was observed that MA (1), MA (2), SAR (12) and the constant are all statistically significant meaning $p < 0{,}05$. And because of this, we form the equation model which is as follows:

$$\hat{Y}_t = 7.42 + 0.39\varepsilon_{t-1} + 0.54\varepsilon_{t-2} - 0.84Y_{t-12}$$

After applying ARIMA $(0,0,2) \times (1,0,0)_{12}$ model to our data set, the ACF and PACF figures of residuals cab be given as seen in figure 4.15 below:

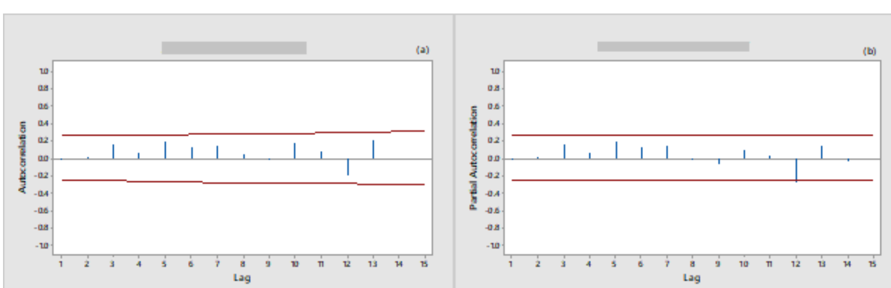

Figure 4.15(a, b): ACF & PACF residuals for ARIMA $(0,0,2) \times (1,0,0)_{12}$

According to figure 4.15 values above, we conclude that ARIMA $(0,0,2) \times (1,0,0)_{12}$ model is proper for our data set because the correlations in this figure are all well within the control limits.

4.2.2.15. ARIMA $(\mathbf{0},\mathbf{0},\mathbf{3}) \times (\mathbf{1},\mathbf{0},\mathbf{0})_{\mathbf{12}}$

Table 4.15: Results of ARIMA $(0,0,3) \times (1,0,0)_{12}$

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
MA 1	-0.49	0.13	-3.78	0.000
MA 2	-0.69	0.12	-5.94	0.000
MA 3	-0.22	0.13	-1.69	0.097
SAR 12	0.77	0.12	6.22	0.000
Constant	10.84	2.96	3.66	0.001
Mean	46.97	12.83		
Number of observations: 60				
Residuals: SS = 4637.57 (back forecasts excluded)				
MS = 84.32		DF = 55		

According to the values of the table above, we observe that MA (1), MA (2), SAR (12) and the constant values are statistically significant i.e. $p < 0.05$, while MA (3) value is statistically insignificant meaning $p > 0.05$. And based on this information, the model equation can be given as follows:

$$\hat{Y}_t = 10.48 + 0.49\varepsilon_{t-12} + 0.69\varepsilon_{t-24} + 0.22\varepsilon_{t-36} + 0.77Y_{t-48}$$

After the application of ARIMA $(0,0,3) \times (1,0,0)_{12}$ model to our data set accordingly, the ACF and PACF figures of residuals can be depicted as in figure 4.16a&b:

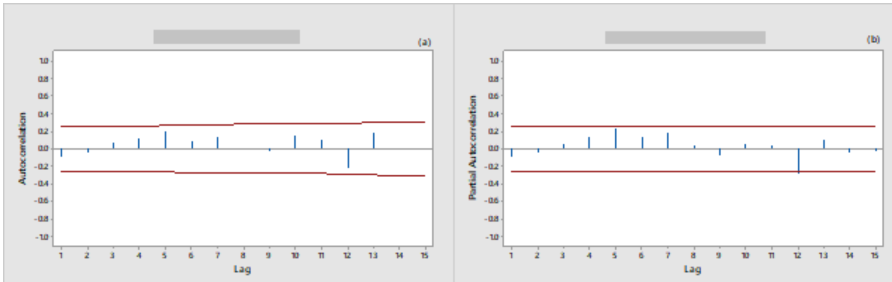

Figure 4.16(a, b): ACF & PACF residuals for ARIMA $(0,0,3) \times (1,0,0)_{12}$

From the values of figure 4.16 above, we conclude that ARIMA $(0,0,3) \times (1,0,0)_{12}$ model is proper for our data set, because the correlations in the figures are within the error limit.

4.2.2.16. ARIMA $(\mathbf{0},\mathbf{0},\mathbf{1}) \times (\mathbf{0},\mathbf{0},\mathbf{1})_{\mathbf{12}}$

Table 4.16: Results of ARIMA $(0,0,1) \times (0,0,1)_{12}$

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
MA 1	-0.27	0.12	-2.16	0.035
SMA 12	-0.86	0.12	-7.26	0.000
Constant	45.39	2.70	16.82	0.000
Mean	45.38	2.70		
Number of observations: 60				
Residuals: SS = 5247.53 (back forecasts excluded)				
MS = 92.06		DF = 57		

According to the values of the table above, MA (1), SMA (12) and the constant values are all statistically significant since $p < 0.05$. Based on this we give the equation of the model to be:

$$\hat{Y}_t = 45.39 + 0.27\varepsilon_{t-1} + 0.86\varepsilon_{t-12}$$

After applying ARIMA $(0,0,1) \times (0,0,1)_{12}$ model carefully to our data set, ACF and PACF figures of residuals cab be given as in figure 4.16a&b:

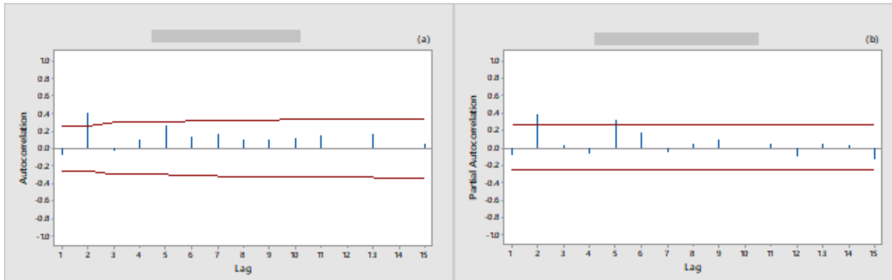

Figure 4.17(a, b): ACF & PACF residuals for ARIMA $(0,0,1) \times (0,0,1)_{12}$

According to the values of the figure 4.17, this model is proper for our data set meaning most of the correlations are within the error limit. But there are some lags some correlations going above the error limit (lag 1 of figure 4.17a and lag 1and 5 of figure 4.17b).

4.2.2.17. ARIMA $(\mathbf{0}, \mathbf{0}, \mathbf{1}) \times (\mathbf{0}, \mathbf{0}, \mathbf{2})_{\mathbf{12}}$

Table 4.17: Results of ARIMA $(0,0,1) \times (0,0,2)_{12}$

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
MA 1	-0.34	0.12	-2.76	0.008
SMA 12	-0.69	0.20	-3.40	0.001
SMA 24	-0.80	0.18	-4.34	0.000
Constant	44.99	3.13	14.38	0.000
Mean	44.99	3.13		
Number of observations: 60				
Residuals: SS = 4299.37 (back forecasts excluded)				
MS = 76.77		DF = 56		

From the table 4.17 values above, we observed that MA (1), SMA (12), SMA (24) and the constant values are all statistically significant meaning $p < 0.05$. And because of this observation, we write the equation of the model as follows:

$$\widehat{Y}_t = 44.99 + 0.34\varepsilon_{t-1} + 0.69\varepsilon_{t-12} + 0.80\varepsilon_{t-24}$$

Then after applying ARIMA $(0{,}0{,}1) \times (0{,}0{,}2)_{12}$ model carefully to our data set, the ACF and PACF figures of residuals can be given in figure 4.17a&b as follows:

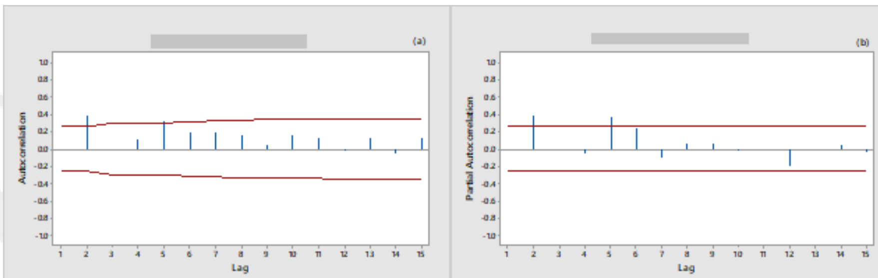

Figure 4.18(a, b): ACF & PACF residuals for ARIMA $(0, 0, 1) \times (0, 0, 2)_{12}$

According to the values of the figures above, we can conclude that ARIMA $(0{,}0{,}1) \times (0{,}0{,}2)_{12}$ model is proper for our data set but not all the correlations are within the control limits as it can be seen that lag 1 of figure 4.18a and lag 1 and 5 of figure 4.18b are above the error limits just like the previous ACF and PACF residuals depicted.

4.3. Method Comparison for Forecasting Patient Volume

In this part we compare each statistical method of generating forecast. First of all, we used the first 60-months data collected from the hospital as a training data to determine the best minimum accuracy measure for our data using the MAPE, MAD, MSD and RSMD statistical forecast accuracy measure for our model. Furthermore, we acquired a 7-months data of January-July of 2017 to compare our model. Now in order to test the performance of these methods i.e. in order to figure out how these methods work on our newly collected data, which is the actual data, we test the performance of these methods by merely using our new data set using the previous methods too. The forecast errors were then calculated by comparing them with the actual 6months data and table 4.18 below shows the summaries of the evaluation of the statistics of all the methods used.

We observed that the first for ARIMA models are the best for our data set because they are lower than the 10% accuracy measure error.

Table 4.18: Percentage error for ARIMA and Winters' using MAPE, MAD, MSD and RSMD.

	MAPE	MAD	MSD	RMSD
$ARIMA$ (1,0,0)	5.4	3.0	14.7	3.83
$ARIMA$ (2,0,0)	5.9	3.3	14.8	3.84
$ARIMA$ $(1,0,0) \times (0,0,1)_{12}$	7.7	4.3	36.8	6.1
$ARIMA$ $(1,0,0) \times (0,0,2)_{12}$	8.1	4.9	34.0	5.8
$ARIMA$ $(0,0,1) \times (0,0,2)_{12}$	10.6	5.8	63.4	7.1
$ARIMA$ (0,0,3)	11.3	6.2	51.1	7.2
$ARIMA$ $(1,0,0) \times (2,0,0)_{12}$	11.9	6.6	75.2	8.7
$ARIMA$ (0,0,2)	14.1	8.3	79.6	8.9
$ARIMA$ $(0,0,3) \times (1,0,0)_{12}$	14.7	8.1	109.1	10.1
$WINTERS'$	15.6	8.8	115.6	10.8
$ARIMA$ $(0,0,2) \times (1,0,0)_{12}$	15.7	8.6	120.7	10.1
$ARIMA$ $(0,0,1) \times (2,0,0)_{12}$	15.8	8.6	116.0	10.8
$ARIMA$ $(0,0,1) \times (2,0,0)_{12}$	15.8	8.7	118.5	10.9
$ARIMA$ $(0,0,1) \times (0,0,1)_{12}$	16.1	8.9	153.2	12.4
$ARIMA$ (0,0,1)	18.2	10.1	118.6	10.9
$ARIMA$ $(0,0,1) \times (3,0,0)_{12}$	30.6	16.4	380.2	19.5
$ARIMA$ $(0,0,1) \times (4,0,0)_{12}$	40.7	21.9	564.1	23.8

4.4. Forecasting Based on Gender

In this part, we select the best performing models for our data set and these models are $ARIMA\,(1,0,0)$, $ARIMA\,(2,0,0)$, $ARIMA\,(1,0,0) \times (0,0,1)_{12}$, $ARIMA\,(1,0,0) \times (0,0,2)_{12}$ having the lowest statistical method comparison. According to the table 4.18 above showing the MAPE, MSD, MAD and the RSMD which are lower than the 10% accuracy measure.

4.4.1. Direct Forecasting

Here we will try to generate forecast using the 60-months training data. While estimating the male patient arrivals. We just consider the male data set and while forecasting the 7-months female patient arrivals, we estimate just the female patient data set using the 4 best performing ARIMA models for our data set.

Table 4.19: MAPE&RMSD ARIMA for male/female direct forecast

ARIMA	MALE		FEMALE	
	MAPE	RMSD	MAPE	RMSD
(1,0,0)	8.35	3.46	19.49	4.65
(2,0,0)	6.61	2.73	19.04	3.87
$(1,0,0)(0,0,1)_{12}$	17.43	8.61	12.43	3.45
$(1,0,0)(0,0,2)_{12}$	13.96	6.52	22.25	4.97

From the table above, we can conclude that direct forecast of ARIMA$(2,0,0)$ works best for our data set with the male patients. While direct forecast of ARIMA$(1,0,0)(0,0,1)_{12}$ works best for our data set with the female patients better than the four best ARIMA models used while applying the overall patient volume to our data set.

The figure below is used to represent the actual demand and the forecasted demand of direct forecasting for male and female patient ARIMA$(2,0,0)\&(1,0,0)(0,0,1)_{12}$.

Figure 4.19(a, b): Male and female actual demand for ARIMA$(2,0,0)\&(1,0,0)(0,0,1)_{12}$ respectively

The figure above shows clearly that while the actual demand is rising the forecasted demand is dropping.

Furthermore, to confirm that this method is actually good for our model we represent it in the ACF and PACF figures below.

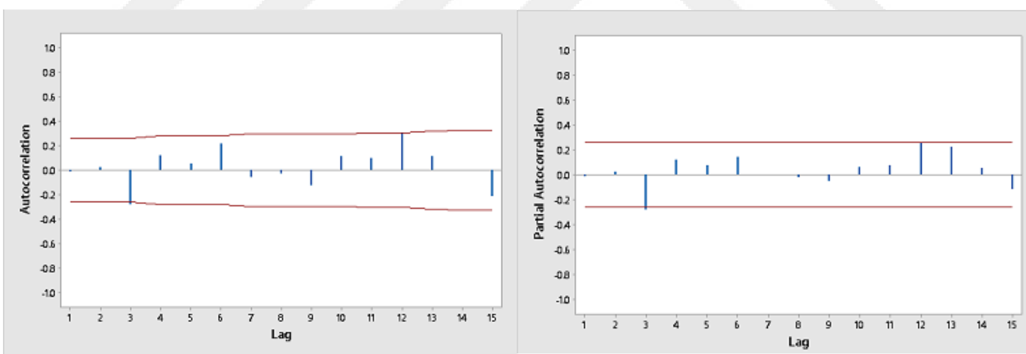

Figure 4.20(a, b): ACF and PACF residuals for ARIMA(2,0,0)

From the figure above, we will notice that the correlations are properly within their control limits, which is indicating that this model is proper for our data set. Although, we did the same thing for the rest of the models but we are showing the figure for this ARIMA. It is the best model for our data out of all the previous when applying the male and female forecasted demand.

4.4.2. Indirect Forecasting

In this part we will be using the forecasted values of the patient volume multiplied by the average percentage of each male and female patients arriving at the hospital making use of the 7-months test data collected from the hospital.

Table 4.20: MAPE&RMSD ARIMA for male/female indirect forecast

ARIMA	MALE		FEMALE	
	MAPE	RMSD	MAPE	RMSD
(1,0,0)	7.04	2.84	18.38	4.16
(2,0,0)	7.46	3.42	17.68	3.93
$(1,0,0)(0,0,1)_{12}$	12.55	5.36	14.06	3.61
$(1,0,0)(0,0,2)_{12}$	11.73	6.12	11.66	3.05

From the table above, we can observe that indirect forecast for ARIMA(1,0,0) works best for our data set using the male and female patient arrivals compared to the MAPE and RMSD of the overall patient volume. Also, from the table above, we see that there is decrease in the RMSD while it increases when we used the overall patient volume data set. And as for indirect forecast for ARIMA$(1,0,0)(0,0,2)_{12}$, RMSD decreases in the table above and MAPE increases compared to the patient volume where RMSD is high while MAPE is low. We also noticed that the indirect forecast works better for our data set than the direct forecast.

The figure below is used to represent the actual demand and the forecasted demand of indirect forecasting for male patient which is ARIMA$(1,0,0)$&$(1,0,0)(0,0,2)_{12}$

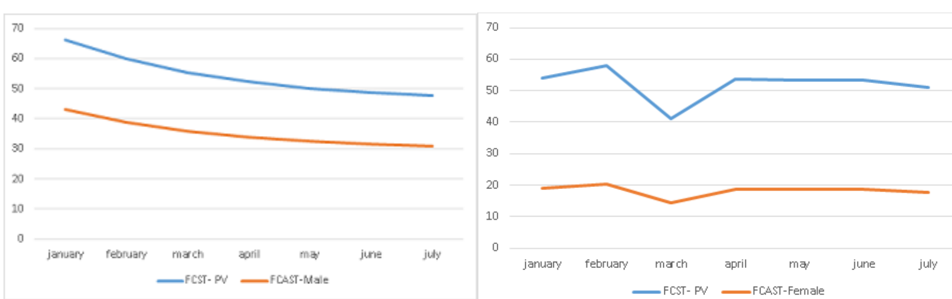

Figure 4.21:(a, b): Male and female actual demand for ARIMA$(1,0,0)$&$(1,0,0)(0,0,2)_{12}$ respectively

The figure below shows that both the male and patient volume for ARIMA(1,0,0) are decreasing. We also depicted this model in ACF and PACF below to confirm that this model is quite okay for our data set and this is shown below:

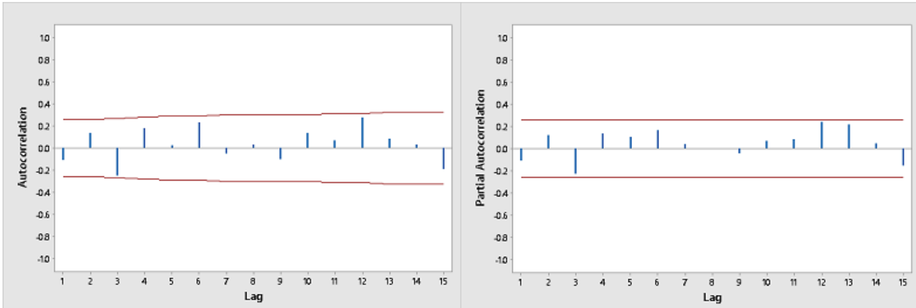

Figure 4.22(a, b): ACF and PACF residuals for ARIMA(1,0,0)

As seen in the figure above that all the correlations are well within their error limit, making this model a good model for our data set.

5. CHAPTER DISCUSSION AND CONCLUSION

Modelling and forecasting are used to provide information in different organisations, one of such organisation is hospital (medical health centres), where planning of resource allocation, staff scheduling and planning future expansion are done based on these methods.

Forecasting method is a process of predicting past and present values into the future. Forecasting patient volume in an emergency department has become quite a difficult task to take on, thus a disparity among emergency department and other employers possibly will result in the former been crowded or even overcrowded which may affect hospital’s staff performances and also patient satisfaction in taking care of them.

Emergency department have been described in different ways in our previous chapters e.g. it is a path way into hospitals for patients in need of quick or immediate emergency care. Emergency medicine is a medical field of study consisting of care for proportionate and unscheduled patients with ailments and or injuries who require urgent medical attention.

The mathematical models which was used in predicting the number of patient volume in emergency department are linear regression and time series analysis (ARIMA) model. Though in our case we made use of the time series analysis to forecast patient volume in emergency department with the aid of monthly data gathered from the hospital (Federal Medical Centre).

The average monthly patient volume showed a seasonally repeated pattern over a 5-year data period collected from the hospital. We categorize our data into male and female type due to the fact that the hospital did not make provision for the full information on their patients. And since our forecasting analysis is for a short-term, we used Winters’ method and ARIMA models to generate the best possible short-term forecast.

Winters’ method is a model that uses three smoothing constants and it is used to predict into the future as long as the series is a seasonal one. It was used to predict the monthly patient arrivals into the emergency department. Our optimal model parameter was set up by using a trial and error methods, after repetitively trying over several periods. Our data set consist of more variations therefore a multiplicative model of Winters’ method was employed because this model is normally used for this type of data with trend and seasonality that increases overtime.

The ARIMA model used include the four stages of model building strategy implementation which are, identification, estimation, model checking and forecasting. The methods of evaluating performance of the data such as MAPE, MSD, RMSD, and MAD were used and the 7-month test data collected from FMC for this present year was also used. The 5-year training data was used to test the performance evaluation of our model and it was discovered that ARIMA works best for our model with an acceptable performance of 5% better than Winters' method with a 15% performance evaluation.

We can then come to the conclusion that, the ARIMA model is a non-seasonal autoregressive model for the first order, following zero seasonal differencing operation and zero moving average i.e. ARIMA $(1,0,0)$ to ARIMA $(10,0,)(0,0,2)_{12}$ are all in between the highly accurate forecast of 5-10 percentage error. This makes them more suitable for modelling our data. This model will be more useful in circumstances where a compelling nonspecific section makes it more demanding to envisage the time series models from its deterministic portions of trend and seasonality.

We tried to forecast the number of male and female patient arrivals at the hospital using the direct forecast method. We concluded that, out of the four best models for the overall patient volume, ARIMA $(2,0,0)$ and ARIMA $(10,0,)(0,0,1)_{12}$ works best for our data set of male and female patient arrivals respectively.

Furthermore, we also use the indirect forecast method, where we actually used the forecasted patient volume multiplied by the average percentage of male and female patient arrivals. And we conclude that, ARIMA $(1,0,0)$ and ARIMA $(10,0,)(0,0,2)_{12}$ models work best for our data set. Therefore, our overall conclusion was that direct and indirect method of forecasting can also be used by the hospital to forecast patient arrivals into the hospital so as to avoid crowding and overcrowding, which leads to efficient and effective use of the hospitals resources. Also, the direct and indirect forecasting both works best for our data set than using the overall patient volume.

The following are the limitations observed during the study. Though there may be other factors affecting the monthly patient arrivals at the emergency department e.g. the availability of other primary health care facilities and their work load which may be used in predicting patient volume in the emergency department. While the second weakness is the use of manual recording i.e. pen and paper register for recording patient arrivals. Although, the process was done regularly in this particular hospital, but it takes too much time and this increases patient's dissatisfaction thus reduces doctors and nurse's efficiencies which can also lead to wastage of medical resources and also the missing data from our data set due to the strike action in which we had to modify our data to suit our use.

We understood from our study that the factors associated with variations of monthly emergency department patient arrivals in the hospital. Therefore, we were able to develop a model to forecast the monthly patient volume. Though, to our knowledge, this is one of the existing few researches works in Nigeria on time series forecasting as was previously mentioned that there have been other researches but only in the developed nations.

The forecasting models we developed for our research can also be extended and used in similar emergency departments in other developing countries around the world, because of this adaptability characteristics. It could be useful in the emergency department of the hospital (FMC) to predict the monthly patient arrivals leading to increase in patient satisfaction and increases staff's effectiveness in discharging their duties.

These methods are useful in healthcare management. Since they can be used for accurate prediction of patient volume, this help to facilitate timely planning of staff deployment and allocation of resources within each department of the hospital. The hospital where the study was carried out is a public hospital, the rural area of the catchment zone for the study is geographically determined. The approach proposed and lessons learned from this experience may assist other hospitals in Kogi state in their emergency departments to carry out their own analysis and to aid planning and budgeting. It allows a basis for macro-planning and allocation of budget by the Ministry of Health, which until now is based on an average aggregated incremental percentage annual growth in Kogi state.

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AKEEM AFOLABI SALAUDEEN

To give a devoted service aimed at realizing the corporate goals and objectives of an organization where personal enhancement, dynamism, and excellence are given a center stage.

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WORK EXPERIENCE

- 09/2016 – 01/2017

Personal Assistant Financial Manager
Societe General
Reims, France
Achievements/Tasks
Reports preparation, Prepare financial statements and forecasting.

- 10/2015 – 01/2016

Librarian (internship)
Yasar University
Izmir, Turkey
Achievements/Tasks
Provision of Information, Manage and organization of library resources.

- 08/2013 – 11/2014

Accountant (National Youth Service Corps)
Badagry Local Government Secretariat
Lagos, Nigeria
Achievements/Tasks
Account Balancing, Voucher Filling and dispatching and also payment of salary to some workers.

- 06/2011 – 07/2012

Assistant Manager
Salaudeen Akeukanwo Investment Ltd
Ilorin, Nigeria
Filling Station (petrol station) where petrol, diesel, gas is being sold.
Achievements/Tasks
Workers welfare, account balancing, salary payment.

- 05/2009 – 06/2010

Distribution Assistant Manager
Kofo-subomi Table Water
Ilorin, Nigeria
Production of bottle and sachet water (drinkable water)
Achievements/Tasks
Oversee product distribution both efficiently and effectively.

EDUCATION

- 05/2008 – 07/2012

BSc. Economics
University of Ilorin
Ilorin, Nigeria
Courses
Economics/Assessment of Household Wealth on Consumption Expenditure.

- 08/2016 – 02/2017

MBA (Erasmus)
Neoma Business School
Reims, France

- **MBA**

Yasar University
02/2015 – 04/2018
Izmir, Turkey
Courses
Masters of Business Administration/ Forecasting Patient Volume in an Emergency Department using Time Series Methods: An Application of a Medical Center in Nigeria.

SKILLS

PERSONAL PROJECTS

- Assessment of Household Wealth on Consumption Expenditure (07/2011 – 06/2012).

We tried assessing the wealth of households in a local government area in known as Ifelodun to know if their consumption is greater than what they earn as salaries.

- Forecasting Patient Volume in an Emergency Department using Time Series Methods: An Application of a Medical Center in Nigeria (02/2017 – 11/2017).

Use of time series analysis to forecast the number of patient volume in the emergency department making use of ARIMA and Winters Methods.

ACHIEVEMENTS

- Nigeria Economics Student Association (University of Ilorin Chapter) (03/2010 – 04/2011)
- Nigerian Institute of Management (Chartered) (06/2014)
- Certificate of Peace-building and Youth by the Rotary Youth Peace Forum (04/2016 – 04/2016)
- Certificate of Attendance of the “EU- Turkey Relations in a New Era?” Seminar (05/2016)

LANGUAGES

- English, Turkish, and French.