Chapter One

1-1 preface:

The importance of determining the demand of medical oxygen by government hospitals in Khartoum state derives from the importance of medical oxygen as one of the most important medical needs necessary to remedial sections which is used in hospitals, especially in the treatment of acute medical patients in the short term in emergency departments such as respiratory diseases, acute pneumonia, asthma and pulmonary congestion due to heart failure or chronic conditions which are required in some cases. These cases need continuity in the use of oxygen, examples include chronic obstructive pulmonary disease, pulmonary fibrosis, sleep disorders. So the oxygen is a major tool of therapy in hospitals and emergency medical management. This research follows the observational analytical approach through field study and collection of data in methods that the field survey and personal interview and statistics. To identify the factors affecting on the demand of medical oxygen, namely : distribution refer to the type of disease (respiratory disease, asthma, pneumonia, etc.- Patient arrives at hospital /hour (Flow Chart) , oxygen transfer rate liter/ min , treatment duration. (Hours) .

This research will contribute to provide accurate information for decision-makers which can helps them in the development of policies leading to the solution of the problem. And to know the real amount of medical oxygen for hospitals to avoid a shortage of the oxygen supply in the future. The privacy and the importance of statistical applications in the study of economic, social phenomena and health, so we seek through this research to apply one of these statistical methods in the study of a demand of medical oxygen by government hospitals in Khartoum. The research takes Box-Jenkins methodology to formulate the demand of the medical oxygen as a method commonly used in time-series models for forecasting analysis. Specifically since the time series is an important statistical topics dealing with the behavior of the phenomena analyzes and interprets over specific periods. The objectives of time series analysis can be summarized to obtain an accurate description of the special features of the process which is generate time series. And build a model to explain the behavior of the time series, and use the results to predict the behavior of the series in the future, in addition to control the process that generated the time series which examines what can happen when you change some of the parameters of the model. This study will contribute to provide accurate information for decision-makers which can helps them in the development of policies leading to the solution of the problem. And to know the real amount of medical oxygen for hospitals to avoid a shortage of the oxygen supply in the future.

1-2 Research Problem:

The problem of this research is how to determine the amount of the demand for medical oxygen by hospitals, and how to avoid a shortage of oxygen to meet the needs of patients, by using a modern statistical methods such as the analysis of time series to predict the size of future demand and logistic regression models to determine the factors affecting on the demand.

1-3 The Importance Of The Research:

This research derives its importance through the use of statistical methods and their practical application in the study of phenomena related to the medical oxygen and builds a statistical model to determine the factors that affect on the size of the demand of medical oxygen. In addition to trying to predict the size of future demand by using the methodology of (Box - Jenkins) for the analysis of time series, to develop solutions of the problem of frequent shortages in medical oxygen in some health facilities through the provision of adequate information.

1-4 Objective of the Research:

Given the importance of medical oxygen in the health system as one of the necessary medical preparations, this research aims to study this vital issue in all its aspects in a scientific and accurate way for the purpose of accessing to the realistic results, to provide information to help in making the right decisions in the provision of this necessary medical preparation, which is important in saving the lives of many patients. Research seeks to achieve the following objectives: -

a- General Objective:

Contribute to enrich the libraries to provide accurate information about medical oxygen for decision-makers which can helps them in the development of policies leading to the solution of the problem.

Specific Objectives :

1- To measure the factors effect on the demand of medical oxygen.

2- Measure the effect of respiratory diseases and other diseases on the demand of medical oxygen.

3- To find the suitable ARIMA model which will use to predict the demand of medical oxygen for Soba University hospital as applied study.

1-5 Research Hypotheses:

1- Respiratory illness requires more demand of medical oxygen than other.

2- The demand on medical oxygen is increasing in the winter without the other seasons.

3- Most age groups of patients need to medical oxygen in hospitals are children under 10 years.

1-6 Data Source

The research data was taken by statistical survey conducted by the researcher , to study the government hospitals in Khartoum state, the survey included an investigation made with a number of 15 government hospitals. They were selected randomly by using the cluster random sampling method, because the sampling frame exists. The study covered the governments hospitals in Khartoum state in (urban & rural) .Data was collected through a questionnaire filled up by conducting a personal interview with responders of hospitals. The researcher used a number of statistical methods to test hypotheses and analyze data under study, which was characterized by diversity , nominal and numerical data , variables also include dependent & independent variables classified into two or more than two categories, taking into account how much the suitability of each statistics method with the test required to get the good results. Also The research data was taken from Soba University hospital which follow to Khartoum University represents one of biggest hospitals in Khartoum

State , such as availability of data leads the researcher to choose the Soba University hospital as applied study of this research .The collected data contained (120) series of observations of monthly consumption of Oxygen, since January 2005 to December 2014.

Data collected from the statistics departments in Khartoum State government's hospitals , planning and statistics management in Ministry of Health in Khartoum State, Federal Ministry of Health, body of medical supplies and the Central Bureau of Statistics.

1-7 Review Studies

Regarding the importance of medical oxygen in people life , a number of theoretical and experimental studies have been conducted in the developed and developing countries. The majority of studies have focused on the importance of medical oxygen and its uses in the treatment of many diseases. There were many previous studies used (Box Jenkins) method in the prediction of time series of an economic nature, and most of the references listed at the end of the research contains practical examples.

However, none of these studies used a (Box Jenkins) methodology in the prediction of the demand of medical oxygen needs by hospitals in Khartoum state.

1) Bradley et al in the Republic of Zambia in 2011 used the method of simulation to estimates the oxygen needs for childhood pneumonia in developing country health systems, he stated that the planning for the reliable and cost-effective supply of a health service commodity such as medical oxygen requires an understanding of the dynamic need or ‘demand’ for the commodity over time.

He mentioned that the developing country health systems, however, collecting longitudinal clinical data for forecasting purposes is very difficult. Furthermore, approaches to estimating demand for supplies based on annual averages can underestimate demand some of the time by missing temporal variability.

Bradley used the methods of a discrete event simulation model which was developed to estimate variable demand for a health service commodity by using the important example of medical oxygen for childhood pneumonia. The model is based on five key factors affecting oxygen demand: annual pneumonia admission rate, hypoxemia prevalence, degree of seasonality, treatment duration, and oxygen flow rate. These parameters were varied over a wide range of values to generate simulation results for different settings. Total oxygen volume, peak patient load, and hours spent above average-based demand estimates were computed for both low and high seasons.

Bradley findings on oxygen demand estimates based on annual average values of demand factors can often severely underestimate actual demand. For scenarios with high hypoxemia prevalence and degree of seasonality, demand can exceed average levels up to 68% of the time. Even for typical scenarios, demand may exceed three times to the average level for several hours per day. Peak patient load is sensitive to hypoxemia prevalence, whereas time spent at such peak loads is strongly influenced by degree of seasonality.

Bradley concluded that a theoretical study is presented whereby a simulation approach to estimating oxygen demand is used to better capture temporal variability compared to standard average-based approaches. This approach provides better grounds for health service planning, including decision-making around technologies for oxygen delivery. Beyond oxygen, this approach is widely applicable to other areas of resource and technology planning in developing country health systems.

2) study conducted by the World Health Organization for oxygen needs in Africa (case study: Gambia). In this study they evaluated two supply options, cylinders and concentrators, in terms of their cost, how well they work and their sustainability. They analyzed the functionality of cylinders and concentrators. Data were collected in 2004–2007 and analyzed in 2005–2008.

Their findings have been previously reported. They found that cylinders were regarded by most users as relatively simple to operate but hard to move, likely to run out without warning and difficult to resupply. Respondents were generally less familiar with operating oxygen concentrators, although they regarded them as easier to move around. They felt, however, that the need for a continuous power supply and the tendency of concentrators to break down were problematic. Both cylinders and concentrators were regarded as expensive, but cylinders were regarded as especially costly by administrators.

The investigators operational experience supported local user observations. Some additional observations were relevant. Effective maintenance and monitoring mechanisms are crucial to success. The Gambia is unlike some countries in that all major health facilities are on or near main roads, so cylinder transport is potentially workable if reliable arrangements can be made.

For the sake of usability, there should be one main method of supply in each facility, with an alternative means of supply as a backup. While solar power has several advantages, including independence from fossil fuels and the careful daily maintenance required for systems powerful enough to run concentrators. So it makes the latter currently impractical for most health facilities in Gambia and other developing countries.

An engineering assessment of the piped oxygen system at the Medical Research Council Hospital showed leakage of around 70% based on the cylinders used and the oxygen delivered over a 4-day period. Most leakage was from the cylinder heads. The cylinder system at the Royal Victoria Teaching Hospital in Banjul also had significant leakage. Cylinder leakage has been repeatedly observed in the Gambia from both free-standing bedside cylinders and piped systems; there are anecdotal reports that problems are greater with older equipment and piped systems. The extent of cylinder leakage was estimated to be 10–80% depending on the kind of system used (piped or direct from the cylinder), the quality of the equipment and the standard of maintenance.

Global experience in comparing the functionality of concentrators and cylinders is summarized in WHO's oxygen therapy handbook. Table 2 represents a refinement of this experience based on the findings of the present study.

Table 1-1. Comparison of the characteristics of oxygen cylinders and oxygen concentrators:

Characteristics	Cylinders	Concentrators
Capital cost	High when regulator and flow meter costs included	High

Running cost	High, particularly if leakage is significant	Low if power is inexpensive High if power is expensive
Ease of use	Some training required	Considerable training required
Reliability	Good	Good on selected models
Physical robustness	Good	Fair
Regular maintenance	Needed	Needed
Technical repairs	Needed (e.g. for regulators, to minimize leakage)	Needed (maintenance staff require specialized training)
Electricity	Not needed	Needed
Continuity of oxygen delivery	Liable to run out	Good as long as power is available
Portability	Poor for large cylinders	Good
Supply system	Transport needed Ordering needed	Transport not needed Ordering not needed

Source: Beverly D. Bradley , Stephen R. C. Howie, Timothy C. Y. Chan,Yu-Ling Cheng. 2014. Estimating Oxygen Needs for Childhood Pneumonia in Developing Country Health Systems. Plos One. 9(2).

Notable differences in the table we used compared to the WHO handbook are that cylinder capital costs approach the high costs of concentrators when regulator-flow meter costs are included; concentrator running costs are high if power costs are high, and training and maintenance are important for cylinders as well as concentrators.(Howie SR. et al. 2009)

3) Several studies conducted by international companies producing medical oxygen, such as Global Oxygen Concentrators Market - Portable Oxygen Concentrators Industry Growth, Analysis And Forecast, 2013 to 2019 Radiant Insights.

4) (WHO / 2010) Oxygen saturation and respiratory rate are the most important clinical parameters to inform the management of severe cases. Continuous monitoring of oxygen saturation is needed and oxygen saturation must be maintained over 90% (92–95% for pregnant women). Respiratory rate above 30 breaths per minute in adults should trigger intervention. The availability of pulse ox meters should be ensured at least in all hospital settings. Supply of (medical or industrial) oxygen must be established and maintained in all hospital settings. High-flow oxygen at 5 or more liters per minute, administered with simple face mask, must be ensured. These are fundamental critical care needs that must be met and be accessible to all patients before any addition to ventilator capacity.

5) There are a number of research, which used the Box Jenkins methodology in time series analysis within and outside of Sudan.

For example: (Shakira Green/2011) used the time series –box Jenkins method to analyze the stock prices ,the empirical results of her study suggested that the uses of the Box-Jenkins Approach to forecast stock prices could be made better by incorporating covariates into the models such as; the introduction of product by an outside company, events that may be occurring in politics, natural disasters, and speculations that are being made about the company in the market.

6) Osama Rabie Amin Soliman / Menoufia University - Faculty of Commerce /2001) conducted research about forecasting loss ratio in property and liability insurance companies using autoregressive and integrated moving average models (ARIMA) for time series analysis. In his study he used the Autoregressive Integrated Moving Average to predict the exact rate of loss of the insurance companies in the Egyptian market. He stated that the best approaches that can be relied upon to determine the rank of (ARIMA) model is the Box – Jenkins approach.

7) Osman Nagar and Monzer Awad published research in the Journal of the University of Damascus Economic and Legal Sciences - Volume 27 - Issue III – 2011) used the Box-Jenkins methodology in time series analysis and forecasting as an applied study about the number of first-grade pupils of primary education in Syria. Their search results showed the models based on the (Box-Jenkins) methodology is preference, so after comparing the analysis models based on the modern methodology (Box-Jenkins) with models based on the traditional method.

8) Another study conducted by Sachin S Mumbare et al (India 2014) about Trends in Average Living Children at the Time of Terminal Contraception: A Time Series Analysis Over 27 Years Using ARIMA (p, d, q) Non seasonal Model. In their study every series was tested for the stationary using augmented Dickey-Fuller test for unit root. Box-Jenkins ARIMA (p, d, q) autoregressive integrated moving averages; non seasonal models were used for the analysis. If the series was found to be non stationary, as interpreted by augmented Dickey-Fuller test, the series was analyzed with $d \geq 1$. The best-fit ARIMA (p, d, q) model was used to forecast the average number of children at the time of terminal

contraception in each group, till 2020.The results were confirmed using expert modeler in SPSS. Forecasting using best-fit ARIMA (p, d, q) non seasonal model has shown that the replacement level of children per couple can be achieved by 2018, for couples opting for terminal contraception. Except Muslims, this will be achieved in between 2016 and 2020 for various strata. This result shows that, though Maharashtra has already achieved replacement level of total fertility rate (TFR), the couples opting for terminal contraception have not yet achieved that target. It was expected because TFR depends on other factors such as age at marriage, number of sterilizations, couple protection rate, infertility prevalence, etc.

9) Another study conducted by Mahmood Moosazadeh et al (Iran 2014) about Forecasting Tuberculosis Incidence in Iran Using Box-Jenkins Models, the present study was designed in order to predict the incidence of TB until 2014 using time series analysis and selection of a suitable model. They mentioned in their study that the box Jenkins models forecast using moving averages, auto regression and a combination of these two methods. The steps in making Box Jenkins models includes; recognizing the pattern, fitting a model and forecasting. The ARIMA (Autoregressive Integrated Moving Average) models are a general class of models also known as Box-Jenkins models. The seasonal ARIMA model (SARIMA) is an expanded form of ARIMA, which allows for seasonal factors to be reflected .In order to examine the nature of data, ts.plot time series graphs, ACF (autocorrelation function) and PACF (partial autocorrelation function) were initially depicted. Through their study they concluded that box-Jenkins (SARIMA) models are suitable for

prediction. The results of this prediction show an increasing trend in total TB incidence in Iran.

10) There is also a study conducted by Rodica Gilca et al (Canada 2012) About the seasonal variations in clostridium difficile infections Are Associated with Influenza and Respiratory Syncytial Virus Activity Independently of Antibiotic Prescriptions a Time Series Analysis in Québec, They mentioned in their study that the incidence and severity of Clostridium difficile-associated diarrhea (CDAD) are increasing in North America and Europe. A Box-Jenkins transfer function model was used to assess the potentially delayed impact of antibiotic prescriptions and of influenza virus and respiratory syncytial virus "RSV" (explanatory series) on the CDAD incidence (explained series). These models have been used to estimate the impact of respiratory viruses and of antibiotic use on health care utilization. They concluded that the univariate models of CDAD incidence, influenza virus, RSV, and antibiotic prescription time series during the period of January 2005 to December 2008, in bivariate analysis, transfer function models showed significant relationships between almost all explanatory time series (respiratory viruses and antibiotic prescriptions) and CDAD incidence with the exception of ciprofloxacin, ofloxacin, and norfloxacin, for which no significant parameter was detected.

11) There is also a study conducted by Arredondo & De Icaza (2011) about the cost of diabetes in Latin America: evidence from Mexico. The main objective was to identify economic burden from epidemiological changes and expected demand for health care services for diabetes in México. The cost evaluation method to estimate direct and indirect costs was based on instrumentation and consensus techniques. To estimate the

epidemiological changes for 2009-2011, three probabilistic models were constructed according to the Box-Jenkins technique. Comparing the economic impact in 2009 versus 2011 ($p< 0.05$), there is a 33% increase in financial requirements. The total amount for diabetes in 2010 (US dollars) will be $778,427,475. It includes $343,226,541 in direct costs and $435,200,934 in indirect costs. The total direct costs expected are: $40,787,547 for the Ministry of Health (SSA), serving to uninsured population; $113,664,454 for insured population (Mexican Institute for Social Security-IMSS-, and Institute for Social Security and Services for State Workers-ISSSTE-); $178,477,754 to users; and $10,296,786 to Private Health Insurance (PHI).

In chapter two the researcher will focus on the issue of medical oxygen demands in Sudan.

Chapter Two

Focus on the Issue of Medical Oxygen in Sudan

2-1 Preface

In the previous chapter the researcher discussed the importance of knowing the factors that affect the demand of oxygen, in order to make sure there is a stable relationship between these factors and the stock of oxygen. Thus, the stability of oxygen demand function may be crucial, especially in the case of Sudan in general and the state of Khartoum specifically because the lack of previous studies and researches on the subject of this research.

The researcher will discusses issue of medical oxygen in Sudan in general with a focus on the state of Khartoum as the case study of the research. Since 50% of the population of the states in Sudan resort to Khartoum State for health services and treatment (Minister of Health in Khartoum State (2015).

So here we must study a number of factors that may affect on the demand of oxygen as population sizes , internal migrations rate to Khartoum state, a number of government health facilities, proportion of morbidity and severity of the diseases which are in need of oxygen therapy and medical oxygen providing sources.

2-2 population distribution in Khartoum state localities :

(Table 2-1shows the population distribution in Khartoum state localities) :

Table 2-1:

State	Total		
Admin Unit (AU)	Total	Male	Female
Khartoum	**5,274,321**	**2,800,024**	**2,474,297**
Karari	**714,079**	**375,001**	**339,078**
Alreef Alshimali	71,284	36,417	34,867
Kararri	404,608	214,639	189,969
Althawraa	238,187	123,945	114,242
Ombaddaa	**988,163**	**532,464**	**455,699**
Alameer	178,850	98,802	80,048
Alssalam	366,344	193,681	172,663
Albooghaa	335,437	180,830	154,607
Alreef Algharbi	107,532	59,151	48,381
Omdurmaan	**513,088**	**273,218**	**239,870**
Wadnoobawi	56,805	29,089	27,716
Hai_Alaraab	38,979	22,335	16,644
Almoaradaa	31,255	15,072	16,183
Abuangaa	53,209	27,960	25,249
Alfitiahaab	59,921	34,278	25,643
Abu_saeed	104,406	56,068	48,338
Alreef Aljanoobi	168,513	88,416	80,097
Bahri	**608,817**	**324,632**	**284,185**
Aljaili	69,377	36,358	33,019
Alsilait	73,441	39,177	34,264
Bahri shimal	287,837	153,103	134,734
Bahri	178,162	95,994	82,168
Shareq_Alneel	**868,147**	**451,466**	**416,681**
Alhaj Yoosof	265,666	139,832	125,834
Shareq Alneel	280,546	149,764	130,782
Wadi Soba	89,596	45,580	44,016
Wad Abusalih	33,920	16,302	17,618
Abudlaig	33,903	16,146	17,757
Alisailaat	20,721	10,552	10,169
Omdawaanban	70,720	35,559	35,161
Alailafoon	73,075	37,731	35,344
Alkhartoum	**639,598**	**343,621**	**295,977**
Alkhartoum shimal	78,736	42,201	36,535
Alkhartoum Gharb	41,930	22,383	19,547
Alkhartoum Wasaat	72,235	38,186	34,049
Alkhartoum Shareq	159,717	85,862	73,855
Alsuhada Wa_soaba	212,103	114,811	97,292
Alshagaraa	74,877	40,178	34,699
Jabal_awliya	**942,429**	**499,622**	**442,807**

Alazhari	248,766	134,856	113,910
Alnaasr	244,837	129,311	115,526
Alkalakla	245,462	129,091	116,371
Jabaal Awliya	203,364	106,364	97,000

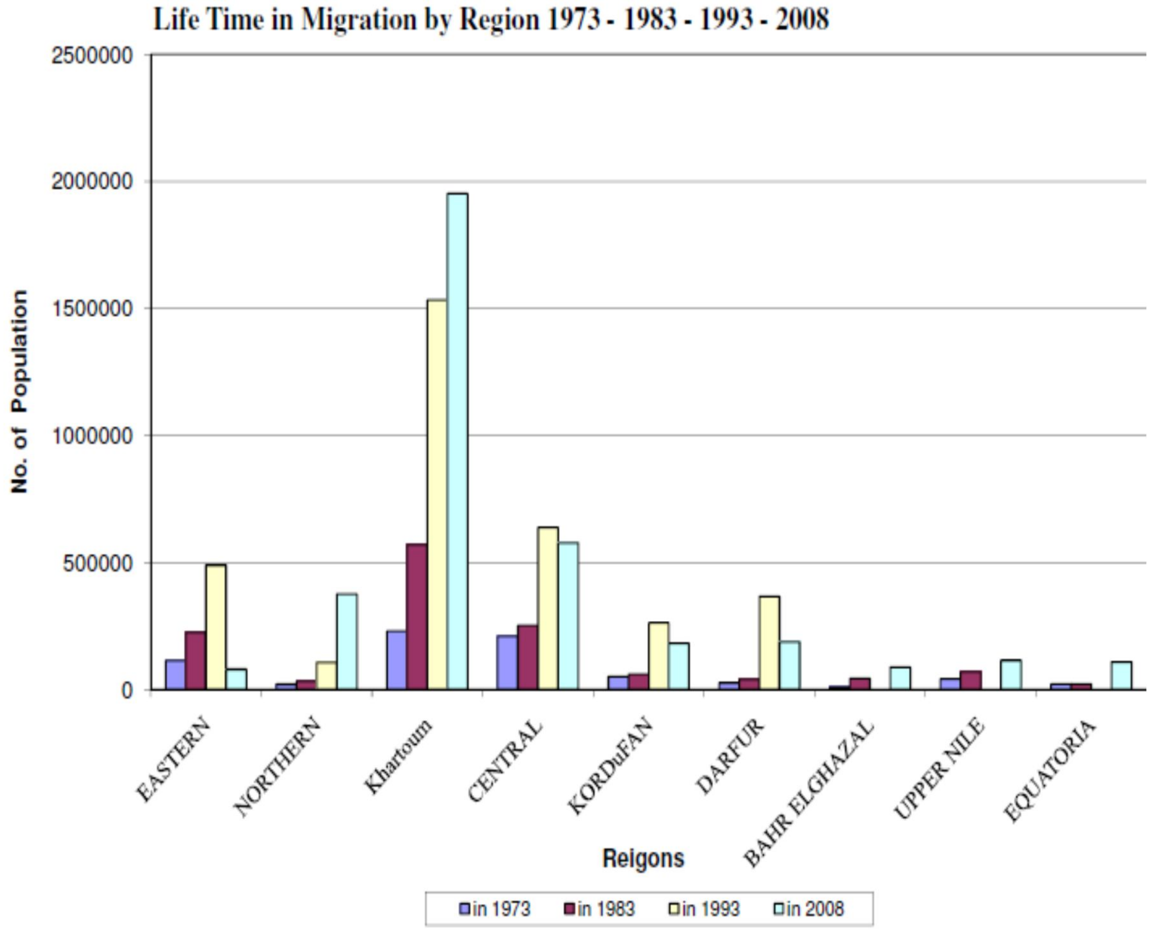
Source: Central Bureau of Statistics Source URLhttp://www.cbs.gov.sd/files.php?id=7#&panel1-2

2-3 Internal Migrations Rate to Khartoum State

In 2012 National Population Council in collaboration with the United Nations Population Fund conducted a study about the number of internally immigrants. The study revealed that the number of internally immigrants increased during the period of the study in Khartoum state. Where migration net rates have increased from 3.7% during the period 1955- 1964, to 7% during the period 1973- 2008. The number of immigrants net rate of Khartoum State about 71% of the total population growth rate of Khartoum State.

The number of migrants from other states increased to 39 % and to 42% in 1983&1993 census respectively. Thus, the upward trend of internal migration to Khartoum State has continued and reached about 2.0 million persons or 49%of all migrants by the time of 2008 census. Figure (2.1) also show that beside Khartoum State; Northern region is also observed to attract population movement according to the data of 2008 census. It received about 3% of all migrants among regions although it has been known as sending region all over the previous censuses since 1973.The remaining regions always have had net losses of internal migrants mainly to Khartoum state or region. (Figure 2-1 shows the Migration Analysis)

Figure 2-1:



Source : Central Bureau of Statistics . Source URL : http://www.cbs.gov.sd/files.php?id=7#&panel1-3

2-4 Government Health Facilities in Khartoum State

All of these numbers of the population meet 35 governmental hospitals, and 13 terminal hospitals in Khartoum state. In addition to that there are 183 governmental health center classified into three sections :(reference family health centers - 41 center), (packages centers - 134 Center), (special units follow the government - 8 units). (table 2-2 shows the governmental hospitals & health care centers in Khartoum)

Table 2-2: shows the governmental hospitals & health care centers in Khartoum

Locality	In Khartoum state					Private health facilities	Organizations
	Hospitals		Health Centers				
	Central Hospital	Terminal Hospitals	Reference Family Health centers	10 Package Center	Private Unit	Clinics	Organizations Unit
Khartoum	13	0	13	11	7	91	11
Jabal_awliya	2	1	8	17	0	7	44
Omdurmaan	9	3	4	16	1	23	20
Karari	2	4	3	17	0	8	39
Ombaddaa	1	0	3	22	0	2	61
Bahri	6	2	7	24	0	18	12
Shareq_Alneel	2	3	3	27	0	8	53
All State	35	13	41	134	8	157	240

(Source: Ministry of Health in Khartoum State. Source URL : http://www.ksmoh.gov.sd/map.html)

2-5 Spread of the Diseases which are Needed Oxygen Therapy

According to the proposals by the Ministry of Health in Khartoum State to create new hospitals and health centers scattered in different sites, this will generate more demand for medical oxygen.

The demand for medical oxygen is urgent to the asthma and pneumonia diseases which are the most spread diseases in the population of the Khartoum State. The medical research results have shown high rates of asthma in Sudan as general about (10%) of injury in Khartoum State (12.5%), mostly among children.(Figures No 2-2 &2-3 Shows the annual reports of school health program in Khartoum State for two years 2013, 2014 ago which are indicted the number of children who have an asthma disease are increased from 803 to 954 cases. (Figures 2-2, 2-3 shows the number of school student have an asthma disease).

Figure 2-2

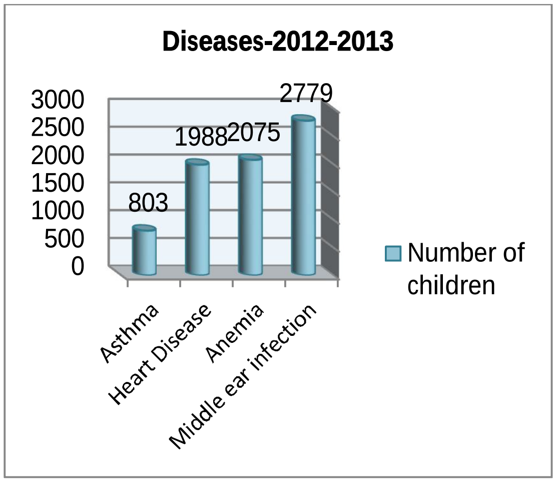
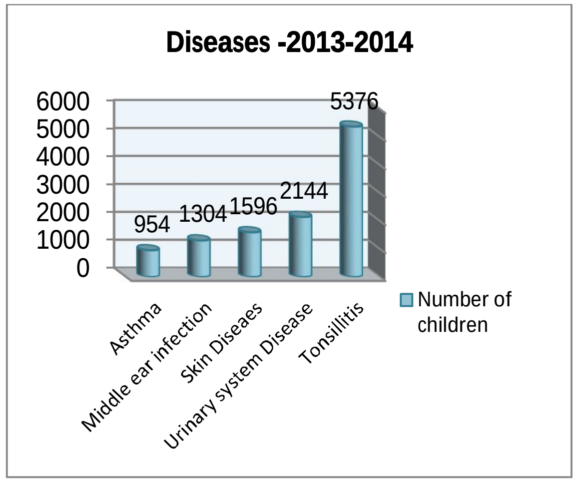


Figure 2-3



(Reference: School Health Annual Report 2012-2013 on *website of the Ministry of Health in Khartoum State*

Source URL: http://www.ksmoh.gov.sd/2013_files/frame.htm *&* http://www.ksmoh.gov.sd/2013-2014_files/frame.htm *)*

In first conference of medical and health research, which was held in Khartoum 2012, experts attributed the high incidence of asthma in Khartoum according to pollution of fumes of cars and factories. Different health reports confirmed that the increasing of infection rates of severe acute respiratory disease in Sudan is increased up to 2 million person per year, 500 thousand of them under the age of five, while the disease reaping the life of 8.3 thousand Sudanese child and cause the detention of 86 thousand hospitals to occupy the second disease which causes deaths among children under the five years old.

Mohamed, Mohamed Gomaa / University of Khartoum, 1997) conducted paper about "Evaluation of asthma severity in school aged children". They mentioned in their paper that an asthma is the commonest cause of chronic ill health in childhood. There study aims at assessing the severity of asthma in school children and evaluating the parents perception of asthma symptoms and disabilities. They found that one hundred and fifty asthmatic school children who were admitted to Khartoum Children Emergency Hospital (K.C.E.H.) and Ahmed Gasim specialist hospital for children, over one year period were enrolled in their study. The children presented in either acute or acute mild, acute moderate or acute severe asthma. A typed questionnaire on medical and social history was completed together with physical examination. There were 84 asthmatic males and 66 females.

Two thirds of the asthmatic school children were found to have mild asthma, 16 percent were moderately asthmatic, and 16 percent were children with severe asthma. One - third of the patients have their first attack during infancy. Over half of the patients experienced the first attack of asthma after the age of four years. Age of first attack showed no correlation with asthma severity.

Parents of asthmatic children were knowledgeable about their children's symptoms. A significant number of school days were lost because of the acute attacks of asthma. Environmental dust and exercise triggered the acute attacks of asthma in most of the patients. Lung function tests gave objective measures to asthma severity. Asthmatic children should be labeled in terms of severity. Those with moderate to severe asthma should have sufficient knowledge on how to predict and deal with emergency situations. They should also have easy access to medical care.

Also global Studies confirmed that one child dies every 20 seconds in the world due to pneumonia disease, than 1.5 million children each year, the reports said that the children who are not immunized against pneumococcal infection with the bacterium are more susceptible to infection.

(Table 2-3 shows the (10) leading diseases treated in health units (outpatients) pre / 1000 Pop. 2013)

Table 2-3: shows the (10) leading diseases treated in health units (outpatients) pre / 1000 Pop. 2013)

Diseases	**Cases**	**Percent**	**Pre / 1000 Pop.**
MALARIA	989946	8	27
PNEUMONIA	976520	8	27
ACUTE TONSILLITIS	609126	5	17
DISORDERS OF URINARY TRACT	495333	4	14
ESSENTIAL	487052	4	13
HYPERTENSION			
DIABETES MELLITUS	444706	4	12
TYPHOID	443170	4	12
DIARRHOEA AND	442623	4	12
GASTROENTERITIS			
INJURIES INVOLVING	365262	3	10
MULTIPLE BODY REGIONS			
OTHER DISEASES OF RISPIRATORY SYSTEM	347009	3	10

Source: Federal Ministry of Health of Sudan. Source URL*http://fmoh.gov.sd/indexAr.php?id=10*

The annual health report in 2013 which was conducted by the Federal Ministry of Health on the health situation in Sudan. The report revealed that the Pneumonia diseases came in second cause among the 10 leading diseases treated in health units, the number of patients attending hospitals for Pneumonia is 976 520 (27%),in comparison to the number of patients attending hospitals for other diseases of respiratory system is 347009(10%), the report also mentioned that the Pneumonia came in first cause among the 10 leading diseases treated in health units for children age (0-4) years, where the number of children attending hospitals are 430813 child (19%).Concerning Khartoum State also the Pneumonia came in second cause among the 10 leading diseases treated in health units, where the number of patients attending hospitals 35443 (14.5%), the report mentioned that the prevalence of Pneumonia in Khartoum State is 65.7 Pre 1000 Pop.

Table (2-4) shows the (10) leading causes of death in hospitals for 2013

Diseases	Deaths	% of death to total deaths
Other Heart Diseases	1331	6
Pneumonia	1137	5
Septicemia	1016	5
Malignant neoplasm's	983	5
Malnutrition	935	4
Lack of expected normal physiol-.develo	866	4
Disease of respiratory system	748	3
Acute renal failure	734	3
Malaria	685	3
Diarrhea &E.G	613	3

Source*: Web side of Federal Ministry of Health of Sudan see :*

http://fmoh.gov.sd/indexAr.php?id=10

Table 2-4 explained that Pneumonia disease came in second cause in the list of 10 diseases caused death in Sudanese hospitals. The number of deaths due to pneumonia is 1137 (5%), the report showed that the number of deaths due to pneumonia in Khartoum State hospitals are 505 (4.1%).

Why don't we take care of these diseases in this research? Because the medical oxygen is one of medications that treating those diseases. Thus the knowledge by the spread rate of respiratory diseases is important for the researcher in order to estimate the medical oxygen needs.

2.6 Acute Severe Bronchial Asthma and Pneumonia

The researcher discusses severe asthma and pneumonia because they are the most diseases that required medical oxygen in their treatment. Nachhattar Singh et al.(2001).They mentioned in their study that the oxygen therapy is required for respiratory failure in many conditions like severe asthma, chronic bronchitis, pneumonia, and myocardial infarction, etc.

Patients with acute severe asthma or status asthmaticus have severe air ways obstruction and inflammation. They are generally hypoxemic. Hypoxemia is corrected by giving oxygen via nasal cannula or face mask at a flow rate of 4-6 L/min to achieve FiO_2 of 35-40%. Flow rate may be adjusted to maintain PaO_2 of about 80 mmHg or more. The risk of hypercarbia and CO_2 narcosis is more in COPD rather than acute severe asthma and in such cases assisted ventilation is required. Administration of sedatives and tranquilizers must be avoided. Sedatives may precipitate the CO_2 retention not only in patients with COPD but also in asthma.

In severe acute viral or bacterial pneumonias, there may be hypoxemia and respiratory failure. Oxygen is given at a flow rate of 4-6 L/min to achieve PaO_2 above 60 mmHg. Bronchial hygiene and treatment with antibiotics and other drugs is meanwhile continued.

2-7 Medical Oxygen Providing Sources

Medical oxygen sources in Sudan depends on a few factories in Khartoum State. Those factories supplies medical gas cylinders in Khartoum State. Their supplies are not sufficient .The government allow private companies to import from outside Sudan to cover the medical oxygen shortage. Different factors affect medical oxygen industry in Sudan as production cost ,transmission and distribution. A number of reports discussed the issue of medical oxygen that occurred in some hospitals in

Khartoum State. And revealed that the oxygen issues that occurred due to lack of supplies or an imbalance in the distribution, and recommended to review the work of the oxygen supply system in hospitals.

Dennis E. Doherty (2013) state that the oxygen providers most providers are firms that have long histories as medical suppliers in your community or surrounding area. Their basic role is to provide the medical hardware that doctors prescribe for their patients, including wheelchairs, stair lifts, crutches, hospital beds, and bedpans.

Of all they provide, portable oxygen equipment is the most challenging for them. Their delivery specialists, customer service personnel, and service technicians must have a basic understanding of oxygen therapy. They should have on staff a respiratory therapist (RT) or other health care professional who understands how to meet a patient's requirements with oxygen.

Like your physician, your oxygen provider must be an approved provider of medical services. Your provider must be approved by your primary insurer, whether it be Medicare or your insurance company. As dedicated as each oxygen provider may be, you will find subtle differences that may help you choose the one who meets your individual requirements.

Their publication said that there are some things to consider before you select a provider include asking questions such as:

- How long have you been in business in this town?
- Do you provide both liquid and compressed portable oxygen systems?
- How do you select a system (liquid vs. compressed and continuous flow vs. pulsating flow) for a patient?
- How often do you deliver oxygen to a home?
- How quickly do you respond to emergency calls—on weekdays and weekends?

- How quickly do you replace defective equipment?
- Do you arrange for oxygen services when I travel?
- How many branches does your company have and where are they located? Provider Accreditation Probably the most important question to ask your proposed provider is about accreditation. An accredited company is one that is responsible to its patients, employees, stockholders, and community. Accredited companies will display their "Certification of Accreditation" prominently. The certificate will be issued by the Joint Commission of Accredited Health Organizations (JCAHO) or one of several other accreditation agencies.

Chapter Three

Time Series Analysis (Box-Jenkins Methodology)

3-1. Preface

In the previous chapter the researcher discussed the issue of medical oxygen in Sudan in general with a focus on the state of Khartoum as the case study of the research. In this chapter the researcher will review the basic concepts of time series analysis and (Box & Jenkins) methodology in the analysis. Also to review the concept of Linear & logistic regression - definition - types of models and the different methods used in estimating the logistic regression models and Chi-Square test. Researcher deals this topics in this chapter as a theoretical & applied framework because they will use in analysis of research data.

3-2. Basic Concepts of Time Series Analysis :

Ratnadip Adhikari (2013) Time series modeling is a dynamic research area which has attracted attentions of researchers community over last few decades. The main aim of time series modeling is to carefully collect and rigorously study the past observations of a time series to develop an appropriate model which describes the inherent structure of the series. This model is then used to generate future values for the series, i.e. to make forecasts. Time series forecasting thus can be termed as the act of predicting the future by understanding the past . Due to the indispensable importance of time series forecasting in numerous practical fields such as business, economics, finance, science and engineering, etc. Proper care should be taken to fit an adequate model to the underlying time series. It is obvious that a successful time series forecasting depends on an appropriate model fitting. A lot of efforts have been done by researchers over many years for the development of efficient models to improve the forecasting accuracy.

3-3. Definition of a Time Series

A time series is a sequential set of data points, measured typically over successive times. It is mathematically defined as a set of vectors $x(t)$, t = 0,1,2,... where t represents the time elapsed . The variable $x(t)$ is treated as a random variable. The measurements taken during an event in a time series are arranged in a proper chronological order.

A time series containing records of a single variable is termed as univariate. But if records of more than one variable are considered, it is termed as multivariate. A time series can be continuous or discrete. In a continuous time series observations are measured at every instance of time, whereas a discrete time series contains observations measured at discrete points of time. For example temperature readings, flow of a river, concentration of a chemical process etc. can be recorded as a continuous time series. On the other hand population of a particular city, production of a company, exchange rates between two different currencies may represent discrete time series.

Usually in a discrete time series the consecutive observations are recorded at equally spaced time intervals such as hourly, daily, weekly, monthly or yearly time separations. The variable being observed in a discrete time series is assumed to be measured as a continuous variable using the real number scale. Furthermore a continuous time series can be easily transformed to a discrete one by merging data together over a specified time interval.

3-4. Components of a Time Series

A time series in general is supposed to be affected by four main components, which can be separated from the observed data. These components are: Trend, Cyclical, Seasonal and Irregular components. A brief description of these four components is given here.

The general tendency of a time series to increase, decrease or stagnate over a long period of time is termed as Secular Trend or simply Trend. Thus, it can be said that trend is a long term movement in a time series. For example, series relating to population growth, number of houses in a city etc. show upward trend, whereas downward trend can be observed in series relating to mortality rates, epidemics, etc. Seasonal variations in a time series are fluctuations within a year during the season. The important factors causing seasonal variations are: climate and weather conditions, customs, traditional habits.

3-5. Time Series Analysis

In practice a suitable model is fitted to a given time series and the corresponding parameters are estimated using the known data values. The procedure of fitting a time series to a proper model is termed as *Time Series Analysis* . It comprises methods that attempt to understand the nature of the series and is often useful for future forecasting and simulation. In time series forecasting, past observations are collected and analyzed to develop a suitable mathematical model which captures the underlying data generating process for the series.

The future events are then predicted using the model. This approach is particularly useful when there is not much knowledge about the statistical pattern followed by the successive observations or when there is a lack of a satisfactory explanatory model. Time series forecasting has important applications in various fields. Often valuable strategic decisions and precautionary measures are taken based on the forecast results. Thus making a good forecast, i.e. fitting an adequate model to a time series is very important. Over the past several decades many efforts have been made by researchers for the development and improvement of suitable time series forecasting models.

3-6. Box-Jenkins Methodology (Theoretical Background)

Spyros Makridakis and Micheale Hibon (1997) The approach proposed by Box and Jenkins came to be known as the Box-Jenkins methodology to ARIMA models, where the letter `I', between AR and MA, stood for the `Integrated' and reflected the need for differencing to make the series stationary. ARIMA models and the Box-Jenkins methodology became highly popular in the 1970s among academics, in particular when it was shown through empirical studies (Cooper, 1972; Nelson, 1972; Elliot, 1973; Narasimham et al., 1974; McWhorter, 1975; for a survey see Armstrong, 1978) that they could outperform the large and complex econometric models, popular at that time, in a variety of situations.

Ion Dobre & Adriana Ana Maria Alexandru (2008) are mentioned in their study that the pioneers in this area was Box and Jenkins who popularized an approach that combines the moving average and the autoregressive models in the book1 .Although both autoregressive and moving average approaches were already known (and were originally investigated by Yule), the contribution of Box and Jenkins was in developing a systematic methodology for identifying and estimating models that could incorporate both approaches. This makes Box-Jenkins models a powerful class of models.

In 1976 George. E .P . Box & Gwilym .Jenkins are revised the edition of their book entitled "Time Series Analysis Forecasting and Control ". The book gave an explanation of the time series models stable and unstable including :

3-7. Autoregressive Models :

A model which can be extremely useful in the representation of certain practically occurring series is the so –called autoregressive model. In this model, the current value of the process is expressed as a finite, linear aggregate of previous values of the process and a shock a_t . Let us denote the value of process at equally spaced times *t , t-1, t-2* , ….By z_t, z_{t-1}, z_{t-2}, …. Also let $\tilde{z}_t$, $\tilde{z}_{t-1}$, $\tilde{z}_{t-2}$, ... be deviations from μ ; for example $\tilde{z}_t = \tilde{z}_t - \mu$. Then

$$\tilde{z}_t = \emptyset_1 \tilde{z}_{t-1} + \emptyset_2 \tilde{z}_{t-2} + \cdots + \emptyset_p \tilde{z}_{t-p} + a_t \qquad (3.7.1)$$

Is called an *autoregressive* (AR) *process of order p*. The reason for this name is that a linear model

$$\tilde{z} = \emptyset_1 \tilde{x}_1 + \emptyset_2 \tilde{x}_2 + \cdots + \emptyset_p \tilde{x}_p + a$$

relating a "dependent" variable z to a set of "independent" variables $x_1, x_2, \dots, x_p$, plus an error term a, is often referred to as a *regression* model, and z is said to be "regressed" on $x_1, x_2, \dots, x_p$. In (3.7.1) the variable z is regressed on previous value of itself; hence the model is *autoregressive*. If we define an *autoregressive operator* of order *p* by

$$\emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p$$

then the autoregressive model may be written economically as

$$\emptyset(B)\tilde{z}_t = a_t$$

The model contains p+2 unknown parameters $\mu, \emptyset_1, \emptyset_2, \dots, \emptyset_p, \sigma_a^2$, which in practice have to be estimated from the data. The additional parameter σ_a^2 is the variance of the white noise process a_t.

Specifically, for an AR (1) process, the sample autocorrelation function should have an exponentially decreasing appearance. However, higher-order AR processes are often a mixture of exponentially decreasing and damped sinusoidal components. For higher-order autoregressive processes, the sample autocorrelation needs to be supplemented with a partial autocorrelation plot. The partial autocorrelation of an AR (***p***) process becomes zero at lag ***p*+1** and greater, so we examine the sample partial autocorrelation function to see if there is evidence of a departure from zero.

This is usually determined by placing a 95% confidence interval on the sample partial autocorrelation plot (most software programs that generate sample autocorrelation plots will also plot this confidence interval). If the software program does not generate the confidence band, it is approximately

$\pm 2 / \sqrt{N}$, with N denoting the sample size. The data is AR (p) if: ACF will decline steadily, or follow a damped cycle and PACF will cut off suddenly after p lags.

3-8. Moving Average Models : The autoregressive model (3.7.1) expresses the deviation $\tilde{z}_t$ of the process as a finite weighted sum of p previous deviations $\tilde{z}_{t-1}, \tilde{z}_{t-2}, \dots, \tilde{z}_{t-p}$ of the process, plus a random shock a_t . Equivalently , as we have just seen , it expresses $\tilde{z}_t$ as an infinite weighted sum of $a's$.

Another kind of model, of great practical importance in the representation of observed time series , is the so-called finite *moving average* process. Here we make $\tilde{z}_t$ linearly dependent on a finite number q of previous $a's$. Thus

$$\tilde{z}_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \qquad (3.8.1)$$

Is called a *moving average* (MA) process of order q. The name "moving average " is somewhat misleading because the weights $1, -\theta_1, -\theta_2, \dots, -\theta_q$, which multiply the $a's$, need not total unity nor need they be positive. However, this nomenclature is in common use, and therefore we employ it.

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$$

then the moving average model may be written economically as

$$\tilde{z}_t = \theta(B) a_t$$

It contains q+2 unknown parameters $\mu, \theta_1, \theta_2, \dots, \theta_q, \sigma_a^2$, which in practice have to be estimated from the data.

The autocorrelation function of a MA (q) process becomes zero at lag q+1 and greater, so we examine the sample autocorrelation function to see where it essentially becomes zero. The following table summarizes how we use the sample autocorrelation function for model identification.

The data is MA (q) if: ACF will cut off suddenly after q lags and PACF will decline steadily, or follow a damped cycle. It’s not indicated to build models with:– Large numbers of MA terms – Large numbers of AR and MA terms together You may well see very (suspiciously) high t-statistics. This happens because of high correlation (“co linearity”) among regressors, not because the model is good.

3-9. Mixed Autoregressive -Moving Average Models :

To achieve greater flexibility in fitting of actual time series, it is sometime advantageous to include both autoregressive and moving average term in the model. This leads to the mixed autoregressive –moving average model

$$\tilde{z}_t = \emptyset_1 \tilde{z}_{t-1} + \cdots + \emptyset_p \tilde{z}_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \qquad (3.9.1)$$

or

$$\emptyset(B)\tilde{z}_t = \theta(B)a_t$$

which employs p+q+2 unknown parameters μ ; , $\emptyset_1, \ldots, \emptyset_p; \theta_1, \ldots, \theta_q$ σ_a^2 , that are estimated from the data.

In practice, it is frequently true that adequate representation of actually occurring stationary time series can be obtained with autoregressive, moving average or mixed models , in which p and q are not greater than 2 and often less than 2.

Non stationary models. Many series actually encountered in industry or business exhibit non stationary behavior or particular do not vary about a fixed mean. Such series may nevertheless exhibit homogeneous behavior of a kind. In particular, although the general level about which fluctuations are occurring may be different at different times, the broad behavior of the series, when differences in level are allowed for, may be similar. Such behavior may be represented by generalized autoregressive operator $\varphi(B)$, in which one or more of the roots of the zeroes of the polynomial $\varphi(B)$ (that is one or more of the roots of the equation $\varphi(B)$= 0) is unity. Thus the operator $\varphi(B)$ can be written

$$\varphi(B) = \emptyset(B)(1 - B)^d$$

where $\emptyset(B)$, is a stationary operator. Thus a general model, which can represent homogeneous non stationary behavior, is of the form

$$\varphi(B)z_t = \emptyset(B)(1 - B)^d\, z_t = \theta(B)a_t$$

that is

$$\emptyset(B)w_t = \theta(B)a_t \qquad (3.9.2)$$

where

$$w_t = \nabla^d z_t \qquad (3.9.3)$$

Homogeneous non stationary behavior can therefore be represented by a model which calls for the *d'th* difference of the process to be stationary. In practice d is usually 0,1 or at most 2. The process provides a powerful model for describing stationary and non stationary time series and is called an *auto-regressive integrated moving average* (ARIMA) *process*, of order (*p*,*d*,*q*).

3-10. **Auto-regressive Integrated Moving Average (ARIMA) process**:

The process is defined by

$$w_t = \emptyset_1 w_{t-1} + \cdots + \emptyset_p w_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \qquad (3.10.1)$$

with $w_t = \nabla^d z_t$. Note that if we replace w_t by $z_t - \mu$, when $d = 0$, the model include the stationary mixed model , as a special case , and also the pure autoregressive model and the pure moving average model . The reason for the inclusion of the word "integrated" (with should perhaps more appropriately be "summed") in the ARIMA title , is as follows.

$$z_t = S^d w_t \qquad (3.10.2)$$

where it will be recalled that S is the summation operator defined by

$$S w_t = \sum_{j=0}^{\infty} w_{t-j} = w_t + w_{t-1} + w_{t-2} + \cdots$$

Thus the general autoregressive integrated moving average (ARIMA) process may be generated from white noise a_t by means of three filtering operations, as indicated by the block diagram . The first filter has input a_t, transfer function $\theta(B)$, and output e_t , where

$$e_t = a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} = \theta(B) a_t \qquad (3.10.3)$$

3.11. Box-Jenkins Methodology:

In 1976 George. E .P . Box & Gwilym .Jenkins are revised the edition of their book entitled "Time Series Analysis Forecasting and Control ". The book gave an explanation of the time series models stable and unstable including an auto-regressive integrated moving average (ARIMA) process, of order (p,d,q). The process is defined by:

$$w_t = \emptyset_1 w_{t-1} + \cdots + \emptyset_p w_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \qquad (3.10.1)$$

3.12. Iterative stages in the selection of the model :

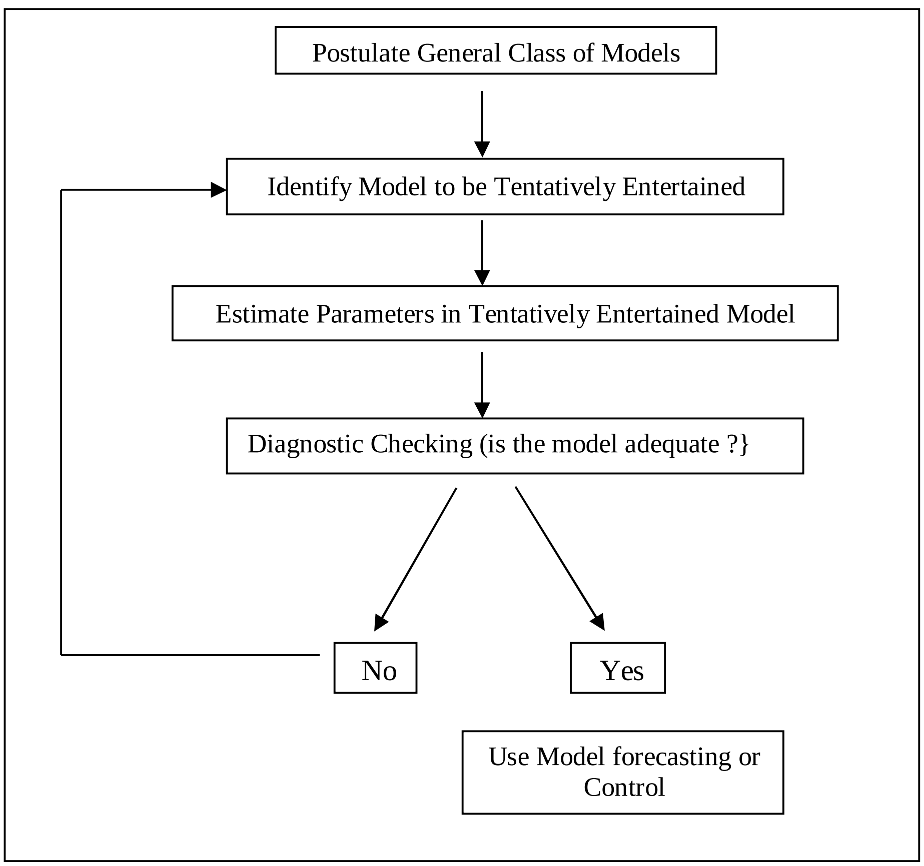


FIG.(3.1) Stages in the iterative approach to model building

Source: Time Series Analysis Forecasting and Control. George. E .P . Box & Gwilym .Jenkins.1976.

(1) From the interaction of theory and practice, a *useful class of models* for the purposes at hand is considered.

(1) Because this class is too extensive to be conveniently fitted directly to data, rough methods for *identifying* subclasses of these models are developed. Such methods of model identification employ data and knowledge of the system to suggest an appropriate parsimonious subclass of models which may be tentatively entertained. In addition, the identification process can be use to yield rough preliminary estimates of the parameters in the model.

   (2) The tentatively entertained model is *fitted* to data its parameters *estimated*. The rough estimates obtained during the identification stage can now be used as starting values in more refined iterative methods for estimating the parameters.

   (3) Diagnostic checks are applied with the object of uncovering possible lack of fit and diagnosing the cause. If any inadequacy is found, the iterative cycle of identification, estimation and diagnostic checking is repeated until a suitable representation is found.

3-13. Box-Jenkins Model Identification

The identification stage is the most important and also the most difficult: it consists to determine the adequate model from ARIMA family models. The most general Box-Jenkins model includes difference operators, autoregressive terms, moving average terms, seasonal difference operators, seasonal autoregressive terms, and seasonal moving average terms. This phase is founded on the study of autocorrelation and partial autocorrelation.

The first step in developing a Box-Jenkins model is to determine if the series is stationary and if there is any significant seasonality that needs to be modeled.

3-14. Stationarity in Box-Jenkins Models

The Box-Jenkins model assumes that the time series is stationary. A stationary series has:. Constant mean Constant variance Constant autocorrelation structure Regression with non stationary variables is a spurious correlation. The random walk $y_t = y_{t-1} + u_t$, $u_t \sim N(0, \sigma^2)$ is is not stationary, since its variance increases linearly with time t.

Stationarity can be assessed from a run sequence plot. The run sequence plot should show constant location and scale. It can also be detected from an autocorrelation plot. Specifically, non-stationarity is often indicated by an autocorrelation plot with very slow decay.

Box and Jenkins recommend differencing non-stationary series one or more times to achieve stationarity. Doing so produces an ARIMA model, with the "I" standing for "Integrated". But its first difference $\Delta y_t = y_t - y_{t-1} = u_t$ is stationary, so y is „integrated of order 1", or y ~ I (1)**.**

3-15. Testing for Non-Stationarity

1. Autocorrelation function (Box-Jenkins approach)-if autocorrelations start high and decline slowly, then series is non stationary, and should be differenced.
2. Dickey-Fuller test

$y_t = a + b\, y_{t-1} + u_t$ would be a non stationary random walk if b = 1. So to find out if y has a "unit root" we regress: $\Delta y_t = a + c y_{t-1} + u_t$ where c = b-1 and test hypothesis that c = 0 against c < 0 (like a "t-test").

3-16. Box-Jenkins Model Estimation

The main approaches to fitting Box-Jenkins models are non-linear least squares and maximum likelihood estimation. Maximum likelihood estimation is generally the preferred technique.

3-17. Box-Jenkins Model Diagnostics

Model diagnostics for Box-Jenkins models is similar to model validation for nonlinear least squares fitting. That is, the error term u_t is assumed to follow the assumptions for a stationary unvaried process. The residuals should be white noise (or independent when their distributions are normal) drawings from a fixed distribution with a constant mean and variance. If the Box-Jenkins model is a good model for the data, the residuals should satisfy these assumptions. If these assumptions are not satisfied, we need to fit a more appropriate model. That is, we go back to the model identification step and try to develop a better model.

Hopefully the analysis of the residuals can provide some clues as to a more appropriate model. The residual analysis is based on:

1. Random residuals: the Box-Pierce Q-statistic: $Q(s) = n \sum r(k)^2 \approx \boldsymbol{X}^{\mathbf{2}}(\boldsymbol{s})$ where r (k) is the k-th residual autocorrelation and summation is over first s autocorrelations.

2. Fit versus parsimony: the Schwartz Bayesian Criterion (SBC): SBC = ln {RSS/n} + (p+d+q) ln (n)/n, where RSS = residual sum of squares, n is sample size, and (p+d+q) the number of parameters.

3.18. Methods used to Analyze the Factors effect on the Oxygen Demand:

To measure the factors affecting the demand of medical oxygen by government hospitals in Khartoum State, the researcher used different kinds of regression models: simple linear regression , binary logistic regression and multinomial logistic regression which are more suitable and advance methods to analyze the data under study.

The researcher also used the chi square test as one of the most important methods and widely used in nonparametric. Researcher used multinomial logistic regression model to test hypothesis of " Respiratory illness requires more demand of medical oxygen than other". In this test oxygen consumption represents dependent variable classified into two categories (High / Low) refer to the general average of consumption . While the type of disease represents independent variable classified into more than three categories, Multinomial logistic regression is used to predict categorical placement in or the probability of category membership on a dependent variable based on multiple independent variables. The independent variables can be either dichotomous (i.e., binary) or continuous (i.e., interval or ratio in scale). Multinomial logistic regression is a simple extension of binary logistic regression that allows for more than two categories of the dependent or outcome variable. Like binary logistic regression, multinomial logistic regression uses maximum likelihood estimation to evaluate the probability of categorical membership.(Dr. Jon Starkweather and Dr. Amanda Kay Moske.2011). Researcher also used chi-square test to test the effect of an other factors on oxygen consumption such as; “the average number of hours spent by the patient in treatment by oxygen ” and “ the oxygen transfer rate to patient it would have been a 2×3 table, or a 3×2 table; it doesn't matter which variable is the columns and which is the rows. It is also possible to do a chi-square test of independence with more than two nominal variables. Jackson et al. (2013) . In addition that the researcher used chi-square test to test :

- The demand on medical oxygen is increasing in the winter without the other seasons.

- Most age groups of patients need medical oxygen in hospitals are children under 10 years. In all statistical testes p - value was considered significant at < 0.05, in all analyses the statistical package for social sciences (SPSS – version 16) was used in the study.

Chapter Four

Applications

4-1.Descriptive Statistics :

The survey covered a number of (15) governmental hospitals in Khartoum State (9 urban & 6 rural) .Were selected randomly , so that the following tables illustrate the results of survey.

Table 4-1 shows that the study described the 66.7% of the hospitals have a high monthly average of medical oxygen consumption , and 33.3% of them have a low consumption. (referring to the general average of consumption ,it detected that the monthly average of a number of patients who take oxygen therapy in hospitals is 334.

Table 4-1

		Frequency	Percent
Valid	High Consumption	10	66.7
	Low Consumption	5	33.3
	Total	15	100.0

Source : by Researcher

Table 4-2 illustrates that the 53.3% of patients spend between (13-24 hr) in the oxygen treatment, while 46.7% of them spend from (1-12 hr).

Table 4-2

		Frequency	Percent
Valid	1-12 hr	7	46.7
	13-24hr	8	53.3
	Total	15	100.0

Table 4-3 illustrates that the 80% of responders said that the appropriate rate of oxygen transfer to the patient is 5 liter/min ,while 20% of them said the appropriate rate is 4 liters/min .

Table 4-3

		Frequency	Percent
Valid	5 liter/min	12	80.0
	4 liters/min	3	20.0
	Total	15	100.0

Table 4-4 shows that the 53.3% of participators in study responded by (Strongly agree) for question of the “A shortage in the supply of medical oxygen in any hospital or any health facility, it may cause deaths”. In addition that 46.7% of them responded by (Agree).

Table 4-4

		Frequency	Percent
Valid	Strongly agree	8	53.3
	Agree	7	46.7
	Total	15	100.0

Table 4-5 illustrates that the 86.7%of participators in study responded by (Strongly agree) for question of the “Medical oxygen concentrators system is better to use in hospitals, than the cylinders system to counter the occurrence of any shortage in supply ”. In addition that 13.3% of them responded by (Agree).

Table 4-5

		Frequency	Percent
Valid	Strongly agree	13	86.7
	Agree	2	13.3
	Total	15	100.0

Table 4-6 shows that the 60%of participators in study responded by (Disagree) for question of the “Medical oxygen produced locally in Sudan is not enough for demand”. In addition that 33.5% of them responded by (Strongly disagree).

Table 4-6

		Frequency	Percent
Valid	Strongly agree	1	6.7
	Disagree	9	60.0
	Strongly Disagree	5	33.3
	Total	15	100.0

Table 4-7 illustrates that the 73.3% of the hospitals use cylinder system in the supply of medical oxygen to the hospital departments . And 13.3% of them use concentrators system , while 13.3% of hospitals use both systems in the same time.

Table 4-7

		Frequency	Percent
Valid	Cylinders	11	73.3
	Concentrators system	2	13.3
	Both Cylinders & Concentrators system	2	13.3
	Total	15	100.0

Table 4-8 Shows that the 60% of Hospital which are covered in study is Central while 40% Terminal Hospital.

Table 4-8

		Frequency	Percent
Valid	Terminal	6	40.0
	Central	9	60.0
	Total	15	100.0

Table 4-9 illustrates that the 60% of participators in study responded by (Disagree) for question of the “ Scarcity of medical oxygen sometimes happens in the markets”. In addition that 26.7% of them responded by (Strongly disagree).

Table 4-9

		Frequency	Percent
Valid	Strongly agree	1	6.7
	Agree	1	6.7
	Disagree	9	60.0
	Strongly Disagree	4	26.7
	Total	15	100.0

Table 4-10 Shows that the 53.3% of participators in study responded by (Winter) for question of the "In which season the demand of medical oxygen increases ". While 13.3% of them responded by (Summer) And 33.3% of responders said that it is non seasonal .

Table 4-10

		Frequency	Percent
Valid	Summer	2	13.3
	Winter	8	53.3
	Non seasonal (All months)	5	33.3
	Total	15	100.0

Table 4-11. illustrates that the 53.3% of responders said that the most age groups of patients who need medical oxygen as a treatment in hospitals who are from children less than 10 years , while 46.7% of responders said that they are from the persons who have more than 30 years.

Table 4-11

		Frequency	Percent
Valid	< 10 years	8	53.3
	> 30 years	7	46.7
	Total	15	100.0

Table 4-12 Shows that the 73.3% of participators in study responded by (Respiratory diseases) for question of the "Which diseases require more demand of medical oxygen than other in treatment". While 13.3% of them responded by (Heart diseases) and 13.3% of responders said that (Surgeries).

Table 4-12

		Frequency	Percent
Valid	Respiratory diseases.	11	73.3
	Heart diseases	2	13.3
	Surgeries	2	13.3
	Total	15	100.0

Table 4-13. illustrates that the 80.0% of participators in study responded by (No) for question of the "In the last five years, Is a shortage of medical oxygen occurred in the hospital? ". While 20% of them responded by (Yes).

Table 4-13

		Frequency	Percent
Valid	Yes	3	20.0
	No	12	80.0
	Total	15	100.0

Table 4-14 denotes that from those who are responded by (yes) 6.7% of them said that it is happened only one time, in addition that 13.3% of them said that the shortage of medical oxygen happened in their hospitals between (2-5) times.

Table 4-14

		Frequency	Percent
Valid	Only one time	1	6.7
	Between (2-5) times	2	13.3
	NA	12	80.0
	Total	15	100.0

4-2. Results of Analyze the Factors effect on the Oxygen Demand:

Table (4-15) shows that the result of measuring the effect of a number of patients who take oxygen therapy, on a monthly average of medical oxygen consumption in hospitals per m^3, by referring to the p -value, which is < 0.05 as in table - (4-15) this means that there is a statistically significant difference . Consequently, the factor of a number of patients who take oxygen therapy in a month affect monthly average of medical oxygen consumption in hospitals per m^3 .Hospitals that receive a large number of patients consume more amount of medical oxygen.

Table (4-15) Coefficients

Model		Un standardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1666.113	465.795		3.577	.003
	How many number of patients who taking oxygen therapy in a month.	3.598	.892	.746	4.034	.001

Source : by Researcher

Table (4-16): Chi-Square Tests					
	Value	Df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	7.500a	1	.006		
Continuity Correction	4.219	1	.040		
Likelihood Ratio	8.282	1	.004		
Fisher's Exact Test				.022	.022
Linear-by-Linear Association	7.000	1	.008		
N of Valid Cases	15				

Source : by Researcher

Table (4-16) shows the result of measuring the effect of the Monthly average of medical oxygen consumption in hospital on the oxygen transfer rate to patient , researcher detects that there is a significant difference ,since ($p < 0.05$).This means that the factor of oxygen transfer rate to patient affects monthly average of medical oxygen consumption.

Table (4-17) :Chi-Square Tests					
	Value	df	Asymp. Sig.(2-sided)	Exact Sig. (2-sided)	Exact Sig (1-sided)
Pearson Chi-Square	8.571a	1	.003		
Continuity Correction	5.658	1	.017		
Likelihood Ratio	10.720	1	.001		
Fisher's Exact Test				.007	.007
Linear-by-Linear Association	8.000	1	.005		
N of Valid Cases	15				

Table (4-17) shows the result of measuring the effect of the monthly average of medical oxygen consumption in hospital on the average number of hours spent by the patient in treatment, researcher detects that there is a significant difference ,since ($p < 0.05$), this means that the time period which spent by patient in treatment affects monthly average of medical oxygen consumption. Also the results of testing the main hypotheses of this research are illustrated as follows : Table (4-17): illustrates the result of multinomial logistic regression model fitting , which is significant , since (P-value <0.05).

Table (4-17): Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	9.161			
Final	3.049	6.112	1	.013

Source : by Researcher

Table (4-18): Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	6.845	3.796	1	.051
Diseases	9.161	6.112	1	.013

Table (4-18): Shows that the result of Likelihood Ratio Tests , which is significant , since (P-value <0.05).

Table (4-19) shows that the result of measuring the hypothesis which is said that “ the demand of medical oxygen is affected by the difference of diseases ”, so that the researcher detects that the result is a significant ,since

($p < 0.05$), this means that the respiratory illness requires more medical oxygen than others.

Table (4-19) Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	10.909	2	.004
Likelihood Ratio	12.393	2	.002
Linear-by-Linear Association	8.842	1	.003
N of Valid Cases	15		

Source : by Researcher

Table (4-20) shows that the result of measuring the hypothesis which is said that " the demand of medical oxygen is not affected by the difference of the age groups of patients who need medical oxygen as a treatment ", so that the researcher detects that the result is not significant ,since ($p > 0.05$). This means that the children less than 10 years and the adults 30 years or above they are most age groups of patients need medical oxygen therapy equally.(except the age group from 10-30 years).

Table (4-20) : Chi-Square Tests					
	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig.(1-sided)
Pearson Chi-Square	.536a	1	.464		
Continuity Correction	.033	1	.855		
Likelihood Ratio	.537	1	.464		
Fisher's Exact Test				.608	.427
Linear-by-Linear Association	.500	1	.480		
N of Valid Cases	15				

Table (4-21) shows that the result of measuring the hypothesis which is said that " the demand of medical oxygen is not affected by the difference of season of year ", so that researcher detects that the result is not significant ,since ($p > 0.05$).

Table (4-21) : Chi-Square Tests			
	Value	df	Asymp.Sig. (2-sided)
Pearson Chi-Square	.712	2	.700
Likelihood Ratio	.734	2	.693
Linear-by-Linear Association	.658	1	.417
N of Valid Cases	15		

4-3. Results of Modeling Medical Oxygen Demand:

The variable used in the analysis is the medical oxygen consumption from 2005 to the end of 2014 and its available monthly. The source of data is the Monthly demand of oxygen by Soba University Hospital In Khartoum.

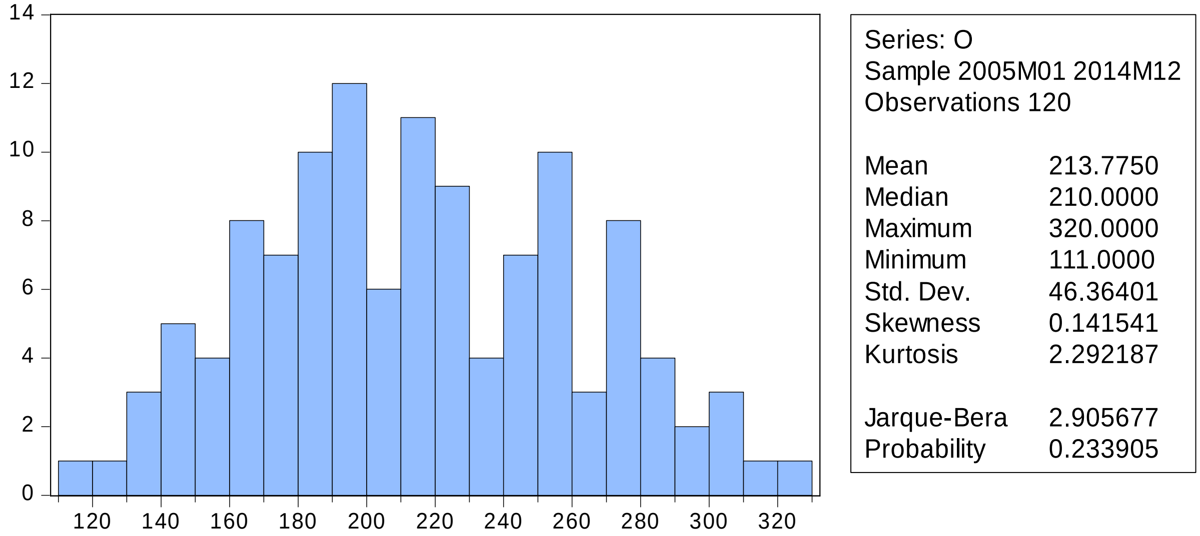
4-4. Stationary Test:

Table:4-22						
					Sample: 2005M01 2014M12	
				Included observations: 120		
Prob	Q-Stat	PAC	AC		Partial Correlation	Auto-correlation
0.000	37.996	0.556	0.556	1	.|**** |	.|**** |
0.000	69.519	0.282	0.504	2	.|** |	.|**** |
0.000	92.234	0.107	0.426	3	.|* |	.|*** |
0.000	125.66	0.282	0.515	4	.|** |	.|**** |

<table>
<tr><td>0.000</td><td>143.73</td><td>-0.050</td><td>0.377</td><td>5</td><td>.|. |</td><td>.|*** |</td></tr>
<tr><td>0.000</td><td>161.03</td><td>0.031</td><td>0.367</td><td>6</td><td>.|. |</td><td>.|*** |</td></tr>
<tr><td>0.000</td><td>176.64</td><td>0.066</td><td>0.347</td><td>7</td><td>.|. |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>191.73</td><td>-0.003</td><td>0.340</td><td>8</td><td>.|. |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>205.89</td><td>0.076</td><td>0.328</td><td>9</td><td>.|* |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>221.35</td><td>0.077</td><td>0.341</td><td>10</td><td>.|* |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>232.88</td><td>-0.033</td><td>0.293</td><td>11</td><td>.|. |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>241.85</td><td>-0.025</td><td>0.257</td><td>12</td><td>.|. |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>250.82</td><td>0.014</td><td>0.256</td><td>13</td><td>.|. |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>261.53</td><td>0.045</td><td>0.279</td><td>14</td><td>.|. |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>271.52</td><td>0.047</td><td>0.268</td><td>15</td><td>.|. |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>273.50</td><td>-0.215</td><td>0.119</td><td>16</td><td>**|. |</td><td>.|* |</td></tr>
<tr><td>0.000</td><td>281.59</td><td>0.172</td><td>0.239</td><td>17</td><td>.|* |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>290.41</td><td>0.072</td><td>0.248</td><td>18</td><td>.|. |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>303.36</td><td>0.080</td><td>0.299</td><td>19</td><td>.|* |</td><td>.|** |</td></tr>
<tr><td>0.000</td><td>305.79</td><td>-0.130</td><td>0.129</td><td>20</td><td>*|. |</td><td>.|* |</td></tr>
<tr><td>0.000</td><td>309.22</td><td>-0.095</td><td>0.152</td><td>21</td><td>*|. |</td><td>.|* |</td></tr>
<tr><td>0.000</td><td>310.80</td><td>-0.066</td><td>0.103</td><td>22</td><td>*|. |</td><td>.|* |</td></tr>
<tr><td>0.000</td><td>311.88</td><td>-0.095</td><td>0.085</td><td>23</td><td>*|. |</td><td>.|* |</td></tr>
<tr><td>0.000</td><td>311.93</td><td>-0.060</td><td>0.018</td><td>24</td><td>.|. |</td><td>.|. |</td></tr>
<tr><td>0.000</td><td>311.96</td><td>-0.034</td><td>0.013</td><td>25</td><td>.|. |</td><td>.|. |</td></tr>
<tr><td>0.000</td><td>311.96</td><td>0.007</td><td>-0.004</td><td>26</td><td>.|. |</td><td>.|. |</td></tr>
<tr><td>0.000</td><td>311.97</td><td>0.014</td><td>0.011</td><td>27</td><td>.|. |</td><td>.|. |</td></tr>
<tr><td>0.000</td><td>312.16</td><td>0.057</td><td>0.034</td><td>28</td><td>.|. |</td><td>.|. |</td></tr>
<tr><td>0.000</td><td>312.77</td><td>0.061</td><td>0.061</td><td>29</td><td>.|. |</td><td>.|. |</td></tr>
<tr><td>0.000</td><td>312.78</td><td>-0.011</td><td>0.005</td><td>30</td><td>.|. |</td><td>.|. |</td></tr>
<tr><td>0.000</td><td>314.21</td><td>-0.198</td><td>-0.093</td><td>31</td><td>*|. |</td><td>*|. |</td></tr>
<tr><td>0.000</td><td>314.40</td><td>-0.016</td><td>-0.034</td><td>32</td><td>.|. |</td><td>.|. |</td></tr>
<tr><td>0.000</td><td>316.53</td><td>-0.129</td><td>-0.112</td><td>33</td><td>*|. |</td><td>*|. |</td></tr>
<tr><td>0.000</td><td>319.17</td><td>-0.026</td><td>-0.125</td><td>34</td><td>.|. |</td><td>*|. |</td></tr>
<tr><td>0.000</td><td>326.87</td><td>-0.031</td><td>-0.211</td><td>35</td><td>.|. |</td><td>**|. |</td></tr>
<tr><td>0.000</td><td>328.31</td><td>0.039</td><td>-0.091</td><td>36</td><td>.|. |</td><td>*|. |</td></tr>
</table>

Source : By Researcher

Figure:4-1



Source: By Researcher(Monthly registration of oxygen demand of Soba University Hospital In Khartoum).

Table 4-22.& Figure 4-1 Show that the medical oxygen consumption rate of Soba University Hospital In Khartoum from 2005 to 2014 .The first step in developing a Box-Jenkins model is to determine if the series is stationary. For this, we use the autocorrelation function (ACF) and Augmented Dickey-Fuller test (ADF).This section is devoted to the application of Augmented Dickey Fuller of unit root and correlogram tests in testing whether the medical oxygen consumption series is stationary. The correlogram test is one of the most powerful statistical tests used in testing whether the time-series data is stationary, the null hypothesis of the test is that all autocorrelations is equal to zero against the alternative hypothesis at one of the autocorrelations is not equal to zero. The acceptance of the null hypothesis all autocorrelations is equal to zero is an indication of stationarity series. While the Augmented Dickey Fuller test is testing the stationarity of the series under the null hypothesis that the series has a unit root against the alternative hypothesis the series does has a unit root, the acceptance of the null hypothesis is an indication of non-stationarity series.

Table:4-23

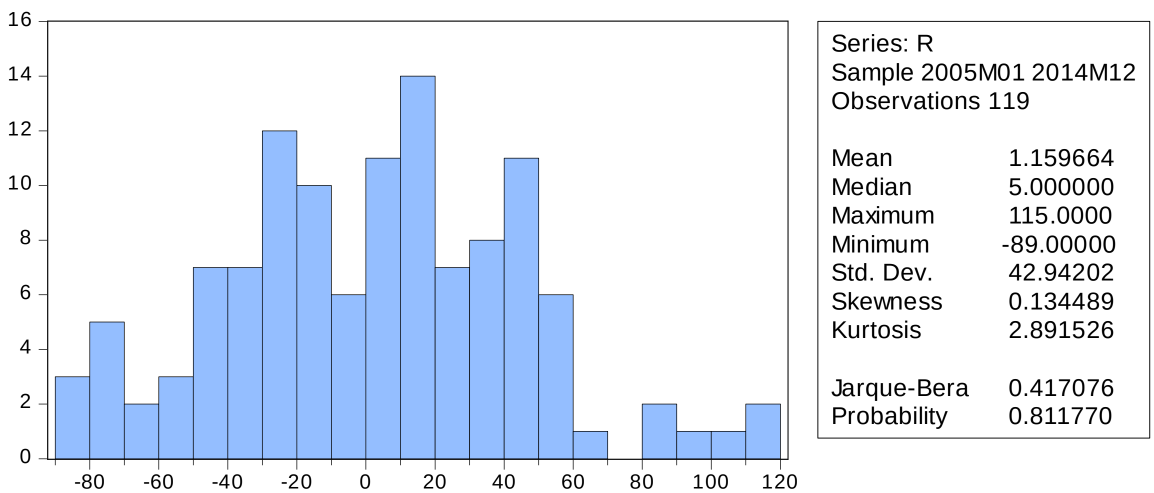
	Null Hypothesis: O has a unit root			
		Exogenous: Constant		
Lag Length: 3 (Automatic - based on SIC, max lag=12)				
Prob.*	t-Statistic			
0.3739	-1.810335	Augmented Dickey-Fuller test statistic		
	-3.487550		1% level	Test critical values:
	-2.886509		5% level	
	-2.580163		10% level	
	*MacKinnon (1996) one-sided p-values.			
	Augmented Dickey-Fuller Test Equation			
		Dependent Variable: D(O)		
		Method: Least Squares		
	Sample (adjusted): 2005M05 2014M12			
	Included observations: 116 after adjustments			
Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.0729	-1.810335	0.088909	-0.160955	O(-1)
0.0000	-4.632861	0.108673	-0.503466	D(O(-1))
0.0034	-2.996282	0.107304	-0.321513	D(O(-2))
0.0004	-3.626825	0.089436	-0.324369	D(O(-3))
0.0589	1.908583	19.17717	36.60121	C
1.215517	Mean dependent var		0.367095	R-squared
42.66631	S.D. dependent var		0.344288	Adjusted R-squared
9.964810	Akaike info criterion		34.54949	S.E. of regression
10.08350	Schwarz criterion		132497.1	Sum squared resid
10.01299	Hannan-Quinn criter.		-572.9590	Log likelihood
2.007821	Durbin-Watson stat		16.09547	F-statistic
			0.000000	Prob(F-statistic)

Source: By Researcher

Table 4-23. show that the Augmented Dickey Fuller unit root test is employed for testing whether medical oxygen consumption series is stationary. Also in determining the order of differencing required in performing time series models. The Augmented Dickey-fuller of unit root test (ADF) with trend, intercept and lag difference of 1 result in above figure shows that the ADF value in absolute terms (**1.810335**) is less than the 1%, 5% and 10% critical values in absolute terms (3.487550, 2.886509 and2.580163) respectively, this results conclude that medical oxygen consumption series has a unit root.

4-5. The identification - the autocorrelation is computed on the first differences series

Figure 4-2



Source by Researcher

Table 4-24

					Sample: 2005M01 2014M12	
						Included observations: 119
Prob	Q-Stat	PAC	AC		Partial Correlation	Auto-correlation
0.000	24.536	-0.448	-0.448	1	***|. |	***|. |
0.000	24.653	-0.213	0.031	2	**|. |	.|. |
0.000	29.944	-0.374	-0.206	3	***|. |	**|. |
0.000	38.746	-0.028	0.265	4	.|. |	.|** |

0.000	41.404	-0.101	-0.145	5	*|. |	*|. |
0.000	41.404	-0.153	0.001	6	*|. |	.|. |
0.000	41.476	-0.014	0.024	7	.|. |	.|. |
0.000	41.546	-0.124	-0.023	8	*|. |	.|. |
0.000	41.656	-0.140	-0.029	9	*|. |	.|. |
0.000	42.864	0.038	0.096	10	.|. |	.|* |
0.000	42.870	0.018	-0.007	11	.|. |	.|. |
0.000	43.226	-0.013	-0.051	12	.|. |	.|. |
0.000	43.347	-0.026	-0.030	13	.|. |	.|. |
0.000	43.411	-0.089	0.022	14	*|. |	.|. |
0.000	47.552	0.208	0.173	15	.|* |	.|* |
0.000	61.157	-0.194	-0.312	16	*|. |	**|. |
0.000	63.842	-0.098	0.138	17	*|. |	.|* |
0.000	64.210	-0.065	-0.051	18	.|. |	.|. |
0.000	73.837	0.120	0.259	19	.|* |	.|** |
0.000	80.901	0.108	-0.220	20	.|* |	**|. |
0.000	81.365	0.034	0.056	21	.|. |	.|. |
0.000	81.587	0.034	-0.039	22	.|. |	.|. |
0.000	81.653	-0.021	0.021	23	.|. |	.|. |
0.000	81.711	-0.020	-0.020	24	.|. |	.|. |
0.000	81.732	-0.048	0.012	25	.|. |	.|. |
0.000	81.900	-0.056	-0.033	26	.|. |	.|. |
0.000	82.087	-0.106	-0.035	27	*|. |	.|. |
0.000	82.128	-0.121	0.016	28	*|. |	.|. |
0.000	84.056	-0.034	0.110	29	.|. |	.|* |
0.000	84.439	0.160	0.049	30	.|* |	.|. |
0.000	90.532	-0.011	-0.193	31	.|. |	*|. |
0.000	95.332	0.152	0.170	32	.|* |	.|* |
0.000	97.365	0.014	-0.110	33	.|. |	*|. |
0.000	99.044	-0.007	0.100	34	.|. |	.|* |
0.000	108.34	-0.047	-0.233	35	.|. |	**|. |
0.000	115.97	-0.047	0.210	36	.|. |	.|* |

Source by Researcher

Figure 4-2&Table 4-24**.** Show that the autocorrelation is computed on the first differences series

Table 4-25

	Null Hypothesis: R has a unit root			
		Exogenous: Constant		
Lag Length: 2 (Automatic - based on SIC, max lag=12)				
Prob.*	t-Statistic			
0.0000	-11.43476	Augmented Dickey-Fuller test statistic		
	-3.487550		1% level	Test critical values:
	-2.886509		5% level	
	-2.580163		10% level	
	*MacKinnon (1996) one-sided p-values.			
	Augmented Dickey-Fuller Test Equation			
		Dependent Variable: D(R)		
		Method: Least Squares		
		Date: 06/27/16 Time: 18:02		
	Sample (adjusted): 2005M05 2014M12			
	Included observations: 116 after adjustments			
Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.0000	-11.43476	0.210293	-2.404647	R(-1)
0.0000	4.936855	0.158149	0.780761	D(R(-1))
0.0000	4.319492	0.086248	0.372548	D(R(-2))
0.4659	0.731668	3.245993	2.374990	C
0.689655	Mean dependent var		0.778962	R-squared
73.25541	S.D. dependent var		0.773042	Adjusted R-squared
9.976666	Akaike info criterion		34.89897	S.E. of regression
10.07162	Schwarz criterion		136409.1	Sum squared resid
10.01521	Hannan-Quinn criter.		-574.6466	Log likelihood
2.030951	Durbin-Watson stat		131.5671	F-statistic
			0.000000	Prob(F-statistic)

Source by Researcher

Table 4-25. Shows the ADF test were also applied to the first difference of medical oxygen consumption series from above figure the result illustrate that the absolute value of the ADF test (11.43476) is grater than the 1%, 5% and 10% critical values in absolute terms (3.487550, 2.886509 and 2.580163) respectively, this result conclude that the first difference of medical oxygen consumption rate series is stationary.

4-6. Model identification and Coefficient Estimates:

ARIMA MODELS

ARIMA(1,1,0)

Dependent Variable: R				
Method: Least Squares				
Date: 06/27/16 Time: 18:09				
Sample (adjusted): 2005M03 2014M12				
Included observations: 118 after adjustments				
Convergence achieved after 3 iterations				
Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.7055	0.378832	2.450138	0.928192	C
0.0000	-5.426164	0.082646	-0.448451	AR(1)
0.838983	Mean dependent var		0.202438	R-squared
42.98180	S.D. dependent var		0.195563	Adjusted R-squared
10.15862	Akaike info criterion		38.55057	S.E. of regression
10.20558	Schwarz criterion		172393.0	Sum squared resid
10.17769	Hannan-Quinn criter.		-597.3587	Log likelihood
2.199712	Durbin-Watson stat		29.44326	F-statistic
			0.000000	Prob(F-statistic)
		-.45		Inverted AR Roots

Source by Researcher

ARIMA(1,1,1)

		Dependent Variable: R		
		Method: Least Squares		
		Date: 06/27/16 Time: 18:12		
	Sample (adjusted): 2005M03 2014M12			
	Included observations: 118 after adjustments			
	Convergence achieved after 9 iterations			
		MA Backcast: 2005M02		
Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.1756	1.362810	0.675630	0.920755	C
0.3770	0.886960	0.119822	0.106277	AR(1)
0.0000	-11.75351	0.069999	-0.822730	MA(1)
0.838983	Mean dependent var		0.341164	R-squared
42.98180	S.D. dependent var		0.329706	Adjusted R-squared
9.984488	Akaike info criterion		35.18985	S.E. of regression
10.05493	Schwarz criterion		142407.5	Sum squared resid
10.01309	Hannan-Quinn criter.		-586.0848	Log likelihood
2.000869	Durbin-Watson stat		29.77507	F-statistic
			0.000000	Prob(F-statistic)
			.11	Inverted AR Roots
			.82	Inverted MA Roots

Source by Researcher

ARIMA(0,1,1)

Dependent Variable: R				
Method: Least Squares				
Date: 06/27/16 Time: 18:14				
Sample (adjusted): 2005M02 2014M12				
Included observations: 119 after adjustments				
Convergence achieved after 7 iterations				
		MA Backcast: 2005M01		
Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.2213	1.229735	0.748853	0.920890	C
0.0000	-12.90649	0.060022	-0.774676	MA(1)
1.159664	Mean dependent var		0.339200	R-squared

42.94202	S.D. dependent var	0.333552	Adjusted R-squared
9.968449	Akaike info criterion	35.05626	S.E. of regression
10.01516	Schwarz criterion	143786.1	Sum squared resid
9.987416	Hannan-Quinn criter.	-591.1227	Log likelihood
1.876080	Durbin-Watson stat	60.05809	F-statistic
		0.000000	Prob(F-statistic)
		.77	Inverted MA Roots

Source by Researcher

ARIMA(1,1,2)

		Dependent Variable: R		
		Method: Least Squares		
		Date: 06/27/16 Time: 18:16		
	Sample (adjusted): 2005M03 2014M12			
	Included observations: 118 after adjustments			
	Convergence achieved after 19 iterations			
		MA Backcast: 2005M01 2005M02		
Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.0230	2.303966	0.374000	0.861683	C
0.0000	11.63787	0.077385	0.900592	AR(1)
0.0000	-13.42382	0.123646	-1.659797	MA(1)
0.0000	5.490656	0.121069	0.664748	MA(2)
0.838983	Mean dependent var		0.350708	R-squared
42.98180	S.D. dependent var		0.333621	Adjusted R-squared
9.986844	Akaike info criterion		35.08692	S.E. of regression
10.08077	Schwarz criterion		140344.5	Sum squared resid
10.02498	Hannan-Quinn criter.		-585.2238	Log likelihood
1.945507	Durbin-Watson stat		20.52525	F-statistic
			0.000000	Prob(F-statistic)
			.90	Inverted AR Roots
		.68	.98	Inverted MA Roots

Source by Researcher

ARIMA(2,1,1)

		Dependent Variable: R		
		Method: Least Squares		
		Date: 06/27/16 Time: 18:19		
	Sample (adjusted): 2005M04 2014M12			
	Included observations: 117 after adjustments			
	Convergence achieved after 9 iterations			
		MA Backcast: 2005M03		
Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.1154	1.586695	0.635640	1.008566	C
0.3235	0.991550	0.122684	0.121647	AR(1)
0.6431	0.464624	0.113194	0.052593	AR(2)
0.0000	-10.81307	0.078483	-0.848647	MA(1)
0.564103	Mean dependent var		0.354292	R-squared
43.06238	S.D. dependent var		0.337150	Adjusted R-squared
9.985561	Akaike info criterion		35.05951	S.E. of regression
10.07999	Schwarz criterion		138896.1	Sum squared resid
10.02390	Hannan-Quinn criter.		-580.1553	Log likelihood
1.962023	Durbin-Watson stat		20.66726	F-statistic
			0.000000	Prob(F-statistic)
	-.18		.30	Inverted AR Roots
			.85	Inverted MA Roots

Source by Researcher

ARIMA(2,1,2)

		Dependent Variable: R		
		Method: Least Squares		
		Date: 06/27/16 Time: 18:21		
	Sample (adjusted): 2005M04 2014M12			
	Included observations: 117 after adjustments			
	Convergence achieved after 18 iterations			
		MA Backcast: 2005M02 2005M03		
Prob.	t-Statistic	Std. Error	Coefficient	Variable
0.1287	1.530354	0.690628	1.056905	C
0.6045	0.519415	0.760278	0.394900	AR(1)

0.9399	-0.075593	0.140944	-0.010654	AR(2)
0.1440	-1.471256	0.763828	-1.123786	MA(1)
0.6960	0.391697	0.629021	0.246386	MA(2)
0.564103	Mean dependent var		0.356372	R-squared
43.06238	S.D. dependent var		0.333385	Adjusted R-squared
9.999428	Akaike info criterion		35.15891	S.E. of regression
10.11747	Schwarz criterion		138448.7	Sum squared resid
10.04735	Hannan-Quinn criter.		-579.9666	Log likelihood
1.973753	Durbin-Watson stat		15.50340	F-statistic
			0.000000	Prob(F-statistic)
	.03		.37	Inverted AR Roots
	.30		.83	Inverted MA Roots

Source by Researcher

After the test of stationary, we conclude that the data is stationary at first difference. The repressor that would be chosen from the model is selected from various iteration for AR(p) and MA(q), the selection is based on observing the ACFs and PACFs. We used E-views for estimating the coefficients and testing the goodness of fit of the model. The search algorithm tried number of different coefficient values, after several iterations, and based on comparing Akaike Information Criteria (AIC), and Schwarz Information criteria (SIC), the best model to forecast medical oxygen demand is ARIMA (0,1,1) since it contains the least AIC and SIC ratios. Table 4-26 shows the AIC and SIC value for various ARIMA (p,d,q) iterations:

Table 4-26

ARIMA (p,d,q).	AIC	SIC
ARIMA (1,1,0)	10.15862	10.205
ARIMA (0,1,1)	**9.968449***	**10.015***
ARIMA (1,1,1)	9.984488	10.054
ARIMA (1,1,2)	9.986844	10.024
ARIMA (2,1,1)	9.985561	10.079
ARIMA (2,1,2)	9.999428	10.117

Source by Researcher

4-7.Forecasting Accuracy:

There are several methods of measuring accuracy and comparing one forecasting method to another, we have selected Root Mean Square Error (RMSE). Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The RMSE, MAE and MAPE are illustrate in the table (4-27).

Table 4-27.

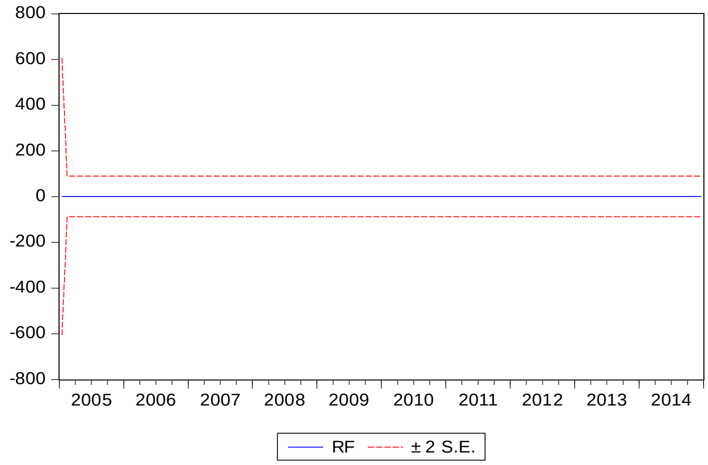
	ARIMA (0,1,1)
RMSE	42.76187
MAE	34.54954
MAPE	97.84004

Source by Researcher

The table 4-27 shows that the Root Mean Squared Error and Mean Absolute Error are less in ARIMA(0,1,1) as compared to other ARIMA models .

4-8. Forecast Result Analysis:

Therefore, the estimation of ARIMA (0,1,1) model is validated, the time series can be described by an ARIMA(0,1,1) process.



Forecast: RF	
Actual: R	
Forecast sample: 2005M01 2014M12	
Included observations: 119	
Root Mean Squared Error	42.76187
Mean Absolute Error	34.54954
Mean Abs. Percent Error	97.84004
Theil Inequality Coefficient	0.978581
Bias Proportion	0.000031
Variance Proportion	NA
Covariance Proportion	NA

Source by Researcher

Forecasting model is : $w_t = a_t - \theta_1 a_{t-1}$

$$MOD = 0.920890 + 0.774676\ a_{t-1}$$

t-Statistic 1.229735 -12.90649

P-value 0.2213 0.0000

DW = 1.876080 , R Square = 0.339200 , SSR= 143786.1

4-9. Discussion

In this aspect the researcher was also interested in studying a number of factors that might have effect on the demand of oxygen as population sizes , internal migrations rate to Khartoum state, a number of government health facilities, proportion of morbidity and severity of the diseases which needed oxygen therapy and medical oxygen providing sources. According to the latest population census 2008 the population of the Khartoum state is (5,274,321). Central Bureau of Statistics.

In 2012 National Population Council in collaboration with the United Nations Population Fund conducted a study about the number of internally immigrants. The study revealed that the number of internally immigrants increased during the period of the study in Khartoum state. Thus, the upward trend of internal migration to Khartoum State continued and reached about 2.0 million persons or 49%of all migrants by the time of 2008 census. All of these numbers of the population meet 35 governmental hospitals, and 13 terminal hospitals in Khartoum state. In addition to that there are 183 governmental health center classified into three sections .The demand for medical oxygen is urgent to the asthma and pneumonia diseases which are the most spreaded diseases in the population of the Khartoum State. The medical research results have shown high rates of asthma in Sudan as general about (10%) of injury in Khartoum State (12.5%), mostly among children, the annual reports of school health program in Khartoum State for two years 2013, 2014 ago which are indicated the number of children who have an asthma disease have increased from 803 to 954 cases. In first conference of medical and health research, which was held in Khartoum 2012, experts attributed the high incidence of asthma in Khartoum according to pollution of fumes of cars and factories. Different health reports confirmed that the increasing of infection rates of severe acute respiratory disease in Sudan is increased up to 2 million per year, 500 thousand of them under the age of five, while the disease reaping the life of 8.3 thousand Sudanese children and causes the detention of 86 thousand hospitals to occupy the second disease which causes deaths among children under the five years old. (Beverly & et .al .2014) “Oxygen demand estimates based on annual average values of demand factors can often severely underestimate actual demand” .

Mohamed, Mohamed Gomaa / University of Khartoum, 1997) conducted research about "Evaluation of asthma severity in school aged children". They mentioned in their paper that an asthma is the commonest cause of chronic ill health in childhood. Two third of the asthmatic school children were found to have mild asthma, 16 percent were moderately asthmatic, and 16 percent were children with severe asthma. One - third of the patients have their first attack during infancy. Over half of the patients experienced the first attack of asthma after the age of four years. The annual health report in 2013 which was conducted by the Federal Ministry of Health on the health situation in Sudan. The report revealed that the Pneumonia diseases came in second cause among the 10 leading diseases treated in health units, the number of patients attending hospitals for Pneumonia is 976 520 (27%),in comparison to the number of patients attending hospitals for other diseases of respiratory system is 347009(10%), the report also mentioned that the Pneumonia came in first cause among the 10 leading diseases treated in health units for children age (0-4) years, where the number of children attending hospitals are 430813 child (19%).Concerning Khartoum State also the Pneumonia came in second cause among the 10 leading diseases treated in health units, where the number of patients attending hospitals 35443 (14.5%), the report mentioned that the prevalence of Pneumonia in Khartoum State is 65.7 Pre 1000 Pop Pneumonia disease came in second cause in the list of 10 diseases caused death in Sudanese hospitals. The number of deaths due to pneumonia is 1137 (5%), the report showed that the number of deaths due to pneumonia in Khartoum State hospitals are 505 (4.1%). Researcher discusses severe asthma and pneumonia because they are the most serious diseases that required medical oxygen in their treatment. Nachhattar Singh et al.(2001).They mentioned in their study that the oxygen therapy is required for respiratory failure in many conditions like severe asthma, chronic bronchitis, pneumonia.

Spyros Makridakis and Micheale Hibon (1997) the approach proposed by Box and Jenkins came to be known as the Box-Jenkins methodology to ARIMA models, where the letter `I', between AR and MA, stood for the `Integrated' and reflected the need for differencing to make the series stationary. ARIMA models and the Box-Jenkins methodology became highly popular in the 1970s among academics, in particular when it was shown through empirical studies (Cooper, 1972; Nelson, 1972; Elliot, 1973; Narasimham et al., 1974; McWhorter, 1975; for a survey see Armstrong, 1978) that they could outperform the large and complex econometric models, popular at that time, in a variety of situations.

Ion Dobre & Adriana Ana Maria Alexandru (2008) are mentioned in their study that the pioneers in this area was Box and Jenkins who popularized an approach that combines the moving average and the autoregressive models in the book1 .Although both autoregressive and moving average approaches were already known (and were originally investigated by Yule), the contribution of Box and Jenkins was in developing a systematic methodology for identifying and estimating models that could incorporate both approaches. This makes Box-Jenkins models a powerful class of models.

Chapter Five

5-1 Conclusion

From the results of the study the researcher believes that it had achieved its objective, because it proved to us that :

- The factor of a number of patients who take oxygen therapy in a month affect a monthly average of medical oxygen consumption in hospitals per m^3.
- The factor of oxygen transfer rate to patient affects monthly average of medical oxygen consumption.
- Time period which spent by patient in treatment affects monthly average of medical oxygen consumption.
- Respiratory illness requires more demand of medical oxygen than others.
- Asthma and pneumonia diseases which are the most spreaded diseases in the people of Khartoum State. that the children less than 10 years and adults 30 years or above they are most age groups of patients need medical oxygen therapy equally (except the age group from 10-30 years).
- Demand of medical oxygen is not affected by the difference of season of year.

The results of the study were identical to the terms of the logic ,Finally the vision is intended to the importance of the awareness issues of medical oxygen especially in governmental hospital in Khartoum state. And the researcher hopes that the study will add a real value to the statistical, societal and medical fields.

In order to develop a univariate Time Series Model, we used medical oxygen consumption of Soba University Hospital in Khartoum state from January 2005 till December 2014.In this research , we have developed systematic and iterative methodology of Box-Jenkins ARIMA forecasting for medical oxygen demand . A unit root test was applied to the long term monthly consumption of oxygen .This concludes that the oxygen demand series is non stationary. After the test of stationary, we conclude that the data is stationary at first difference, E-views software is used for fitting the coefficient of the model, using graphs, statistics, ACFs and PACFs of residuals and after several iterations, the model selected is ARIMA(0,1,1).There are several ways of measuring forecasting accuracy; we have used Mean Absolute Error, Root Mean, Square Error and Mean Absolute Percentage Error. We may use this model for forecasting the medical oxygen demand for future.

5-2 Recommendation

Through research and discussion results come out the following recommendations:

1) A review of the oxygen gas distribution in hospitals and follow up the inventory process.
2) The use of cylinders system and work on the transition to the production of oxygen Center in hospitals

3) The decision makers allow and encourage investment in the field of medical oxygen industry with an emphasis on ensuring the safety and security measures.
4) The establishment of a specialized unit management and distribution of oxygen gas inside hospitals and health centers.
5) Develop plans and strategies and programs that aim to reduce the incidence of respiratory disease rates, especially (Asthma, pneumonia).
6) Develop a model that can be used to predict the demand of medical oxygen, which constitutes a scientific base to put good plans to avoid any shortage of oxygen in the hospitals of Khartoum State.
7) The oxygen issues that occurred due to lack of supplies or an imbalance in the distribution, and recommended to review the work of the oxygen supply system in hospitals.
8) Promote and provide input medical services, especially oxygen in rural hospitals in Khartoum State
9) Based on previous studies we need to promote school health program in schools in the state of Khartoum and to provide special care for children with asthma and other respiratory diseases.

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Appendixes:

In the name of Allah, the most Gracious, the most Merciful

Medical Oxygen Consumption Forum

Dear Responder:

You are invited to participate in a PhD research titled **" Statistical analysis of the demand of medical oxygen by government hospitals in Khartoum State and the factors affecting on the demand"** A topic in statistic Applied at the **Sudan University of Science & Technology** .

Could you please, fill out this forum ? The data collection will provide useful information regarding the study; mean while your response to the forum will be kept confidential and will be used for the purpose of the present study. Thank you for your time to assist the researcher in his educational endeavors.

Mr.Walid Sayed Mohamed Hamed Karar- the researcher

Name of Responder (optional):………………………………………………………………………………

Date:………25-April 2016 ……………………………………………القياس اسطوانة 6 متر مكعب…………

Place of work (hospital name)…Soba Hospital………………………………………………………

Job title:……

The amount of medical oxygen that consumed by your hospital (per/ Liters) in the period from January 2005-December 2014

Month / Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
January	147	150	165	189	276	245	210	200	320	200
February	186	174	165	196	256	180	170	221	240	185
March	219	141	141	248	252	260	227	270	285	270
April	144	189	121	292	220	220	275	196	200	245
May	132	162	171	216	276	255	190	209	235	210
June	147	156	189	256	256	190	240	177	190	300
July	162	162	166	184	252	295	245	194	180	255
August	192	207	178	224	220	300	220	215	210	260
September	138	192	193	232	244	280	190	230	250	270
October	168	189	169	252	268	255	305	180	238	310
November	156	138	156	208	224	270	216	215	217	280
December	196	111	171	216	228	270	175	210	190	285

University Of Khartoum
Soba University Hospital
Date:……
Medical Records & Statistics

List of Government Hospitals in Khartoum state that covered by study and the monthly average of oxygen amount that consumed by hospitals

N	Hospital Name	The amount of Oxygen Per - m^3	No of Patients	No Hours	Oxygen transfer rate
1	Khartoum Hospital	780	45	24	5 liter/min
2	El- shaab Hospital	2700	195	24	5 liter/min
3	Ibrahim Malik Hospital	5400	750	24	4 liter/min
4	Soba Hospital	3600	120	24	5 liter/min
5	Turkish hospital	1980	85	24	4 liter/min
6	Omdurman Hospital	4500	360	It depend	5 liter/min
7	Omdurman children incidents Hospital	3960	1140	24	5 liter/min
8	Omdurman Obstetrics Hospital	4050	300	24	5 liter/min
9	Abu-anjh Hospital	1440	120	24	5 liter/min
10	Albulk Hospital	840	80	24	5 liter/min
11	Bahri Hospital	5400	300	24	5 liter/min
12	Ahmed Qassem Children's Hospital	6300	1350	24	5 liter/min
13	Elban Jadeed Hospital	960	23	24	5 liter/min
14	Sharq Elneel Hospital	870	120	24	5 liter/min
15	Um Dwaban Hospital	210	15	24	6 liter/min