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PATIENT'S INFLUX AT OUTPATIENT MEDICAL LABORATORY (OPML);

FORECASTING OF PATIENT'S INFLUX AT MAYO HOSPITAL, LAHORE USING ARIMA MODEL

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ABSTRACT… Objective: Uni-variate time series data analysis has been reported in medical literature for prediction the patients volume, emergency overcrowding, stay length in hospital on surgical procedure and bed occupancy in hospital wards, patients influx or patients arrival, moreover to estimate the cost of hospital stay or any medical or surgical procedure. **Design:** The present study was designed to fit an appropriate uni-variate ARIMA model (Box-Jenkin methodology) to forecast the patient's incoming at OPML, Mayo Hospital, Lahore. **Setting:** Mayo Hospital Lahore, **Period:** September 2009 to December 2013 were used for fitting the best model. **Method**: Time series data of male, female and peads patients coming/reporting in OPML, OPD. **Result & conclusion:** The appropriate model for male and female data was found as ARIMA (1, 0, 1) and for peads as ARIMA (1, 1, 1) after residuals diagnostic checks. The estimated number of male patients for Month of January2014 is 632 whereas the actual incoming of male patients in the month of January, 2014 was 649, which shows that the estimated model has ability to forecast the number of incoming patients accurately. It is now concluded that the fitted ARIMA model can be used to forecast the patients incoming to OPD Medical Laboratory for future planning and management.

Key words: Forecast, Medical Time Series Data, ARIMA Model, Box-Jenkin Methodology

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INTRODUCTION

Hospital Outpatients Medical Laboratory (OPML) overcrowding has become a severe problem throughout Pakistan as case around the world, which consequents in increasing care costs, causing stress in Medical Laboratory Professionals (MLP's), patients and their attendants and also affecting adversely the outcomes of medical & clinical systems. One side of problem is the difficulty of anticipating the timing and magnitude of overcrowded condition.[1] Modeling and forecasting the patients volume using some most appropriate statistical, may provide useful information for hospital administration and Medical Laboratory Professionals (MLP's), which may be useful in planning, expansion, allocating resources and recruitment.[1,2,3,4]

Uni-variate time series data analysis has been reported in medical literature for prediction of the patients volume, emergency overcrowding, stay length in hospital on surgical procedure and bed occupancy in hospital wards, patients influx or patient arrival, moreover to estimate the cost of hospital stay or any medical or surgical procedure.[5,6,7]

Several authors used time series data analysis techniques like AR (Autoregressive) MA (Moving Average) ARIMA (Autoregressive Integrated Moving Average) model in forecasting the patient's arrival behavior and trend in hospitals. Time series Models and techniques provide better results than traditional approaches such as descriptive statistics, multiple regression and ANOVA.[8,9,10]

OBJECTIVE OF STUDY

The health/patients related data, which is collected over a sequence of time at regular interval normally shows a non-stationary behavior and clinical researchers are often interested to forecast the future occurrence of such related phenomena. The ARIMA model has the ability to handle the non-stationary time series data to forecast. The objective of this study is to forecast the incoming of patients at OPML, OPD, Mayo Hospital Lahore.

ARIMA MODEL

The most popular model for forecasting of uni-variate time series data is ARIMA model, which was introduced by Box-Jenkin in 1976.[11,12] As many researchers used this model for forecasting of different medical phenomenon, in paper we have used ARIMA model for forecasting of future incoming of patients at OPML Mayo Hospital Lahore. The ARIMA model is combination of two time series processes Autoregressive (AR) and Moving Average (MA). The ARIMA model is defined as

$$X_t = \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + ... + \Phi_p X_{t-p} + Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + ... + Z_q \theta_{t-q} \quad (1)$$

The ARIMA model is used for integrated stationary process and is best when time series is non-stationary, the non-seasonal ARIMA is classified as ARIMA(p,d,q)[13-16], the process X_t is said to be ARIMA

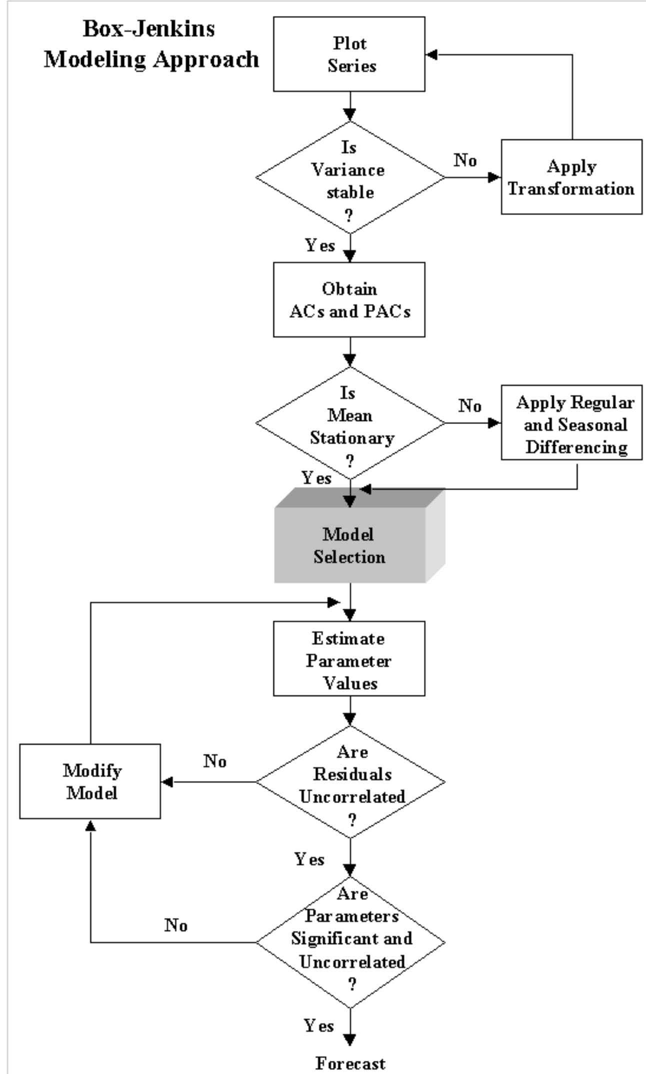
if $\nabla^d X_t = (1-B)^d X_t$ (2)

$$W_t = \alpha_1 W_{t-1} + \alpha_2 W_{t-2} + ... + \alpha_p W_{t-p} + Z_t + \theta_1 Z_{t-1} + ... + \theta_q Z_{q-t}$$

We can say, the process is stationary after differencing the process "d" times, normally in practice the "d" is taken one. The ARIMA model building procedure which is also known as Box-Jenkin method, involves the following four steps:-

1. Identification of Model
2. Estimation of model parameters
3. Diagnostic checks (model checking)
4. Forecasting

The flow chart of the model is as below:



The short description of each step is as

IDENTIFICATION OF MODEL

In this step, the order of respective time series model is determined, the order of differencing "d", the order of AR process which is "p" and order of MA process is "q". The model is written as ARIMA (p,d,q). Differencing is the procedure which is used to remove the trend in the time series data, we use differencing to remove the trend in the data. It is critical to difference the time series data, until stationary is getting done. Any seasonal variation can be removed through some appropriate seasonal differencing. The stationarity of time series means that arithmetic mean, variance and autocorrelation remain same over time. It means that if time series data is stationary, then the arithmetic mean of any major subset of data of time series data does not significantly different of any other major subset of the series.[17,18]

Value of "d"

The order of differencing "d" is estimated through autocorrelation plot, when the autocorrelations die out quickly, then the appropriate value of "d" can be found. Most statistical forecasting methods are based on the assumption that the time series can be turned into approximately stationary using of some sort of mathematical transformations. The first difference of a time series is the series of changes from one period to the next. If X(t) denotes the value of the time series X at period t, then the first difference of X at period t is equal to $X_{(t)}$-$X_{(t-1)}$.

Value of 'p"

The order of AR (Autoregressive) process "p" is determined from PACF (partial autocorrelation function) of the differenced series. If the PACF cut off after few lags (a period of time between one event and another), the last lag with the larger value would be the estimated value of "p".

Value of 'q"

The order of MA (moving average) process is determined from ACF (auto correlation function) of differenced time series.

PROCEDURE FOR CHECKING THE STATIONARITY

The time plot, correlogram and unit root test are used to test the stationarity of the time series data. The time plot steers us about the trend of data, whereas correlogram guides us regarding the order of ARIMA model and behavior of the series. The unit root test is performed to determine the significance of stationarity in the data. There are several available statistical methods for unit rot test of non-seasonal time series data, those tests are Dickey-Fuller (DF), Augmented Dickey-Fuller (ADF, 1979)Zivot (1992), and KwaitKowski (1992). For a given data set, there may be several model with different orders, for example ARIMA (1, 1, 1), ARIMA (2, 1, 1) and more, but final model is selected using statistical tools like AIC (**Akaike information criterion**) and BIC(**Bayesian information criterion) or Schwarz criterion.** The AIC and BIC are tools to measure the goodness of fit of model. Among number of models, that model is considered best which has lower value of AIC or BIC.[18-25]

ESTIMATION OF PARAMETERS

Next step after the tentative ARIMA model is the estimation of parameters. Least square or maximum likelihood method can be used to estimate the parameters. The parameters are estimated on the basis of previously available data.

DIAGNOSTIC CHECK

The tentative suggested ARIMA model is then checked for reasonable fit to the data or we can say that in this stage, we verify the statistical adequacy of the fitted model. Statistically an adequate model must satisfy the four properties:-

i) The estimated parameters must be significant
ii) All Auto Regression (AR) estimated parameters must be within the "bound of statisonarity". the condition of bound stationarity is as:-

AR order	Condition of bound
AR(1)	$\lvert\Phi_1\rvert < 1$
AR(2)	$\lvert\Phi_2\rvert < 1$
	$(\Phi_2 - \Phi_1) < 1$
	$(\Phi_2 + \Phi_1) < 1$

iii) All Moving Average (MA) estimated parameters must lie in the bound of stationarity.
iv) The Residuals of model (the unexplained part of data) should be least and R^2 should be maximum; the possible test for minimum residuals, Q-statistic is introduced by Ljung-Box (Ljung and Box 1979, Harry 1993).

FORECASTING

The eventual target of ARIMA model is to forecast. When the model has undergone all the diagnostic check, the model becomes adequate for forecasting. Various researches showed that ARIMA model performs lustrous in term of forecasting as compared to other models.

DATA ACQUISITION AND ANALYSIS STRATEGY

The data of monthly patient's records at OPML OPD Mayo Hospital, Lahore from September 2007 to December 2013 was acquired for modeling. Computer software E-view 5 (Quantitative Micro Software (QMS), USA) and R (Freeware software)[26] was used to analyze the time series data. The following tools were used for fitting the model.

Step	Statistical Tools	Purpose
Identification	Time Plot Correlogram	To see the trend in data To show the relationship among current and past observations
	Unit Root Test	To check the stationarity in the data
Estimation	Maximum Likelihood estimation (MLE)	To estimate the parameters
Diagnostic Check	R^2 , Goodness of fit AIC, BIC	To find out the most appropriate model
Forecasting and its Accuracy	RMSE(Root Mean Squared Error), MAE(Mean Absolute Error), MAPE(Mean Absolute Percentage Error),	To forecast and check the accuracy in model using forecast error term

RESULTS

The original time series data of male, female and peads patients were plotted to observe the behavior or trend in the data, plotting of data is considered a first step to identify the time series model. The line charts of data are shown in Fig 1-4.

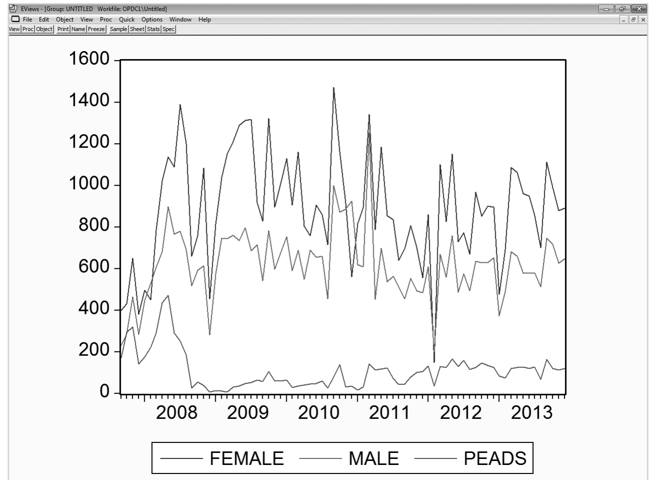


Fig-1. The time plot of all data

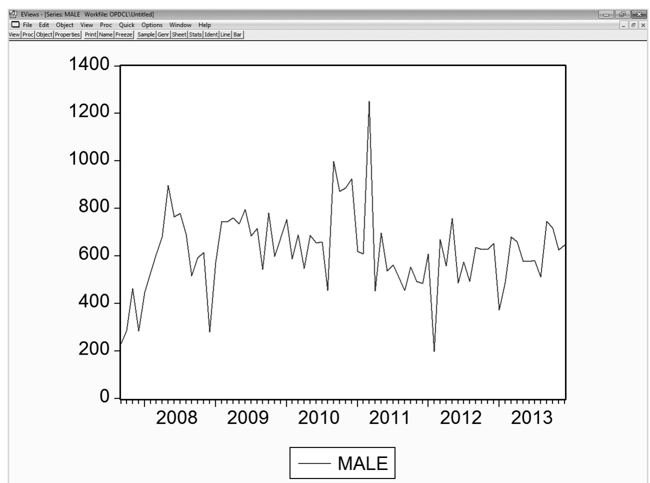


Fig-2. The time plot of male data

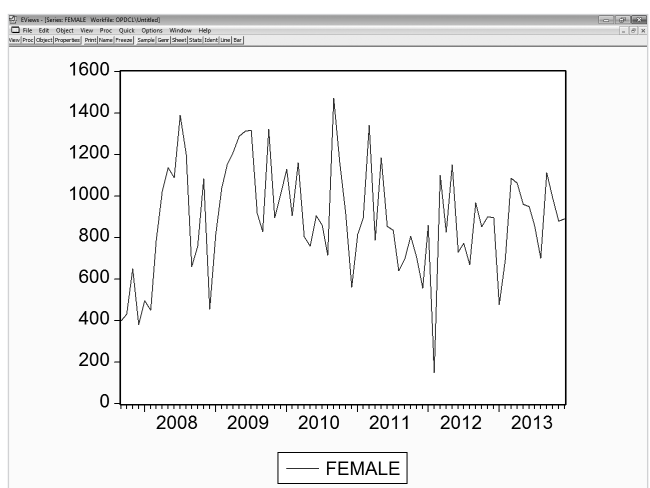


Fig 3. The time plot of female data

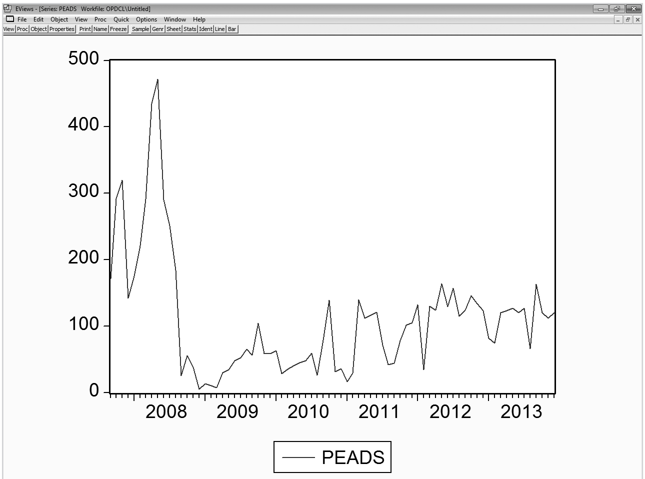


Fig 4. The time plot of peads data

STATIONARITY CHECKING

Autocorrelation function **(ACF)** is a widespread tool to check the stationarity of the time series data. ACF & PACF are also used to propose the order of the tentative model. The correlogram (graph of ACF & PACF) of male and female data is stationary at zero difference (d=0) whereas the pediatrics data is adjusted for stationarity at d=1, shown in Fig 5-8.

Apart from the graphic methods, the ADF unit

Correlogram of FEMALE

Date: 03/13/14 Time: 21:59
Sample: 2007M09 2013M12
Included observations: 76

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.333	0.333	8.7678	0.003
		2	0.270	0.179	14.600	0.001
		3	0.098	-0.041	15.386	0.002
		4	0.057	-0.009	15.656	0.004
		5	-0.066	-0.102	16.024	0.007
		6	0.032	0.082	16.109	0.013
		7	-0.087	-0.090	16.754	0.019
		8	0.084	0.137	17.374	0.026
		9	-0.055	-0.097	17.640	0.040
		10	0.013	0.007	17.656	0.061
		11	0.152	0.218	19.752	0.049
		12	0.185	0.074	22.931	0.028
		13	-0.053	-0.214	23.198	0.039
		14	0.072	0.054	23.691	0.050
		15	-0.043	-0.005	23.869	0.067
		16	-0.053	-0.066	24.147	0.086
		17	-0.140	-0.096	26.124	0.072
		18	-0.076	0.014	26.714	0.085
		19	-0.059	0.027	27.074	0.103
		20	-0.088	-0.134	27.901	0.112
		21	-0.166	-0.042	30.879	0.076
		22	-0.078	-0.050	31.545	0.085
		23	-0.038	0.003	31.703	0.106
		24	-0.075	-0.029	32.344	0.119
		25	-0.113	-0.074	33.826	0.112
		26	-0.003	0.035	33.827	0.139
		27	-0.052	-0.010	34.159	0.161
		28	0.002	0.081	34.160	0.196
		29	-0.052	-0.050	34.507	0.221
		30	-0.023	-0.077	34.576	0.258
		31	-0.013	0.065	34.599	0.300
		32	-0.013	0.058	34.623	0.344

Fig 6. The Correlogram of Female data

Correlogram of MALE

Date: 03/13/14 Time: 21:56
Sample: 2007M09 2013M12
Included observations: 76

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.260	0.260	5.3310	0.021
		2	0.309	0.259	13.002	0.002
		3	0.212	0.097	16.636	0.001
		4	0.084	-0.060	17.213	0.002
		5	0.020	-0.077	17.245	0.004
		6	0.011	-0.008	17.255	0.008
		7	-0.189	-0.201	20.313	0.005
		8	-0.083	-0.008	20.916	0.007
		9	-0.054	0.080	21.170	0.012
		10	0.020	0.128	21.207	0.020
		11	-0.009	-0.012	21.214	0.031
		12	0.109	0.082	22.310	0.034
		13	-0.027	-0.100	22.379	0.050
		14	0.072	-0.012	22.868	0.062
		15	-0.035	-0.097	22.986	0.084
		16	-0.052	-0.051	23.253	0.107
		17	-0.021	0.066	23.297	0.140
		18	-0.033	0.033	23.406	0.175
		19	0.041	0.145	23.583	0.213
		20	0.004	-0.033	23.585	0.261
		21	-0.055	-0.109	23.908	0.298
		22	-0.047	-0.133	24.146	0.340
		23	-0.055	-0.060	24.479	0.378
		24	-0.077	-0.048	25.156	0.397
		25	-0.051	0.065	25.462	0.437
		26	-0.040	0.107	25.653	0.482
		27	-0.136	-0.063	27.907	0.416
		28	0.079	0.147	28.668	0.430
		29	0.048	0.006	28.964	0.467
		30	0.036	-0.060	29.133	0.511
		31	0.064	-0.110	29.673	0.534
		32	0.012	-0.049	29.693	0.584

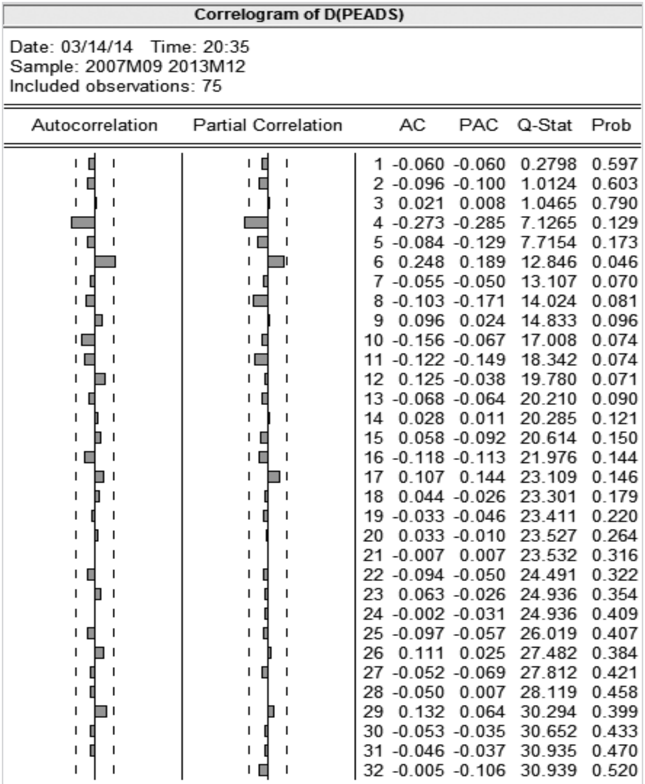
Fig 5. The Correlogram of Male data

Correlogram of PEADS

Date: 03/14/14 Time: 20:36
Sample: 2007M09 2013M12
Included observations: 76

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.806	0.806	51.379	0.000
		2	0.623	-0.077	82.481	0.000
		3	0.475	-0.012	100.79	0.000
		4	0.335	-0.074	110.03	0.000
		5	0.297	0.197	117.39	0.000
		6	0.288	0.047	124.41	0.000
		7	0.175	-0.291	127.04	0.000
		8	0.068	-0.065	127.44	0.000
		9	-0.003	0.064	127.44	0.000
		10	-0.094	-0.094	128.23	0.000
		11	-0.122	-0.026	129.59	0.000
		12	-0.101	0.059	130.54	0.000
		13	-0.108	0.019	131.64	0.000
		14	-0.089	0.041	132.41	0.000
		15	-0.078	-0.051	133.00	0.000
		16	-0.091	0.008	133.81	0.000
		17	-0.059	0.091	134.17	0.000
		18	-0.053	-0.123	134.45	0.000
		19	-0.066	-0.060	134.91	0.000
		20	-0.079	-0.050	135.57	0.000
		21	-0.100	-0.004	136.64	0.000
		22	-0.119	-0.017	138.19	0.000
		23	-0.114	-0.047	139.64	0.000
		24	-0.124	-0.029	141.41	0.000
		25	-0.137	0.025	143.58	0.000
		26	-0.117	0.057	145.20	0.000
		27	-0.137	-0.120	147.47	0.000
		28	-0.144	0.003	150.03	0.000
		29	-0.137	-0.009	152.41	0.000
		30	-0.175	-0.120	156.36	0.000
		31	-0.185	-0.036	160.88	0.000
		32	-0.180	-0.037	165.24	0.000

Fig 7. The Correlogram of Peads data



	AC	PAC	Q-Stat	Prob
1	-0.060	-0.060	0.2798	0.597
2	-0.096	-0.100	1.0124	0.603
3	0.021	0.008	1.0465	0.790
4	-0.273	-0.285	7.1265	0.129
5	-0.084	-0.129	7.7154	0.173
6	0.248	0.189	12.846	0.046
7	-0.055	-0.050	13.107	0.070
8	-0.103	-0.171	14.024	0.081
9	0.096	0.024	14.833	0.096
10	-0.156	-0.067	17.008	0.074
11	-0.122	-0.149	18.342	0.074
12	0.125	-0.038	19.780	0.071
13	-0.068	-0.064	20.210	0.090
14	0.028	0.011	20.285	0.121
15	0.058	-0.092	20.614	0.150
16	-0.118	-0.113	21.976	0.144
17	0.107	0.144	23.109	0.146
18	0.044	-0.026	23.301	0.179
19	-0.033	-0.046	23.411	0.220
20	0.033	-0.010	23.527	0.264
21	-0.007	0.007	23.532	0.316
22	-0.094	-0.050	24.491	0.322
23	0.063	-0.026	24.936	0.354
24	-0.002	-0.031	24.936	0.409
25	-0.097	-0.057	26.019	0.407
26	0.111	0.025	27.482	0.384
27	-0.052	-0.069	27.812	0.421
28	-0.050	0.007	28.119	0.458
29	0.132	0.064	30.294	0.399
30	-0.053	-0.035	30.652	0.433
31	-0.046	-0.037	30.935	0.470
32	-0.005	-0.106	30.939	0.520

Fig 8. The Correlogram of Peads data at d=1

root test (also a very popular method to check the stationairty of the data) was also performed to confirm the stationarity of the data shown in table-I.

Variable	ADF test statistic (p value) d=0	ADF test statistic (p value) d=1
Male	-6.80(0.000)	-9.7589 (0.000)
Female	-6.52 (0.000)	-14.07 (0.000)
Peads	-2.85 (0.06)	-8.97 (0.000)

Table-I. ADF test results

MODEL SPECIFICATION

The ACF & PACF of male, female and Peads data is shown in Fig 5-8. The correlogram of male and female data indicated that the order of model is not more than 2 lags and order of peads data is not more than 3 lags. So the tentative/proposed model may be ARIMA(1,0,0), ARIMA(1,0,1), ARIMA(1,1,1), ARIMA(2,0,1), ARIMA(2,1,1). All parameters of the models are estimated using Maximum Likelihood Estimation (MLE) method. The diagnostic checks were also done using Ljung & Box methods. In addition to that, the best model was selected on the following criteria with maximum R^2 and minimum AIC/BIC, RMSE, MAE and MAPE.

MAXIMUM LIKELIHOOD ESTIMATION OF PARAMETERS

The summary of estimated parameters is in table-II for male, table-III for females and table-IV for peads data.

Parameters	Proposed models for male data		
	ARIMA (1,0,0)	ARIMA(1,0,1)	ARIMA(1,1,1)
C	625.51	640.88	-0.456
AR	0.259	0.734	0.209
MA	---------- ---------	-0.567	-0.99

Table-II. Summary of estimated parameters of proposed model

Parameters	Proposed models for female data		
	ARIMA (1,0,0)	ARIMA (1,0,1)	ARIMA (1,1,1)
C	897.17	919.84	-0.734
AR	0.33	0.746	0.308
MA	-------------- -----	-0.567	-0.997

Table-III. Summary of estimated parameters of proposed model

Parameters	Proposed models for Peads data		
	ARIMA (1,0,0)	ARIMA (1,0,1)	ARIMA (1,1,1)
C	106.92	107.91	-2.422
AR	0.82	0.78	0.455
MA	--------------- ----	0.075	-0.107

Table-IV. Summery of estimated parameters of proposed model

3.4 DIAGNOSTIC CHECK

The summary of diagnostic tools of all proposed models are shown in Table-V for males and best model is selected as ARIMA (1, 0, 1) , for female in Table-VI and best model is ARIMA(1,0,1) and for Peads in Table-VII. 7, and best model is

ARIMA(1,1,1) (4)

Parameters	Proposed models for male data		
	ARIMA (1,0,0)	ARIMA (1,0,1)	ARIMA (1,1,1)
R^2	0.072	0.170	0.040
BIC	13.07	13.02	13.12
AIC	13.01	12.93	13.02
RMSE	161.04	154.33	203.19
MAPE	22.65	21.09	97.23
MAE	117.86	112.04	139.67

Table-V. the summary of diagnostic check for male data

Parameters	Proposed models for female data		
	ARIMA (1,0,0)	ARIMA (1,0,1)	ARIMA (1,1,1)
R^2	0.166	0.169	0.036
BIC	13.93	13.93	13.98
AIC	13.87	13.83	13.89
RMSE	253.38	242.54	301.78
MAPE	30.54	29.21	100.014
MAE	197.90	190.92	232.54

Table-VI. The summary of diagnostic check for female data

Parameters	Proposed models for peads data		
	ARIMA (1,0,0)	ARIMA (1,0,1)	ARIMA (1,1,1)
R^2	0.564	0.655	0.70
BIC	10.89	10.95	11.00
AIC	10.83	10.86	10.81
RMSE	85.34	85.95	54.48
MAPE	151.54	152.37	107.61
MAE	61.33	61.67	36.22

Table-VII. The summary of diagnostic check for peads data

The fitted ARIMA (1, 0, 1) for male data can be described as:

$$X_t = \phi_1 X_{t-1} + Z_t + \theta_1 Z_{t-1}$$
$$X_t = 640.8 \;\; + 0.734 X_{t-1} - 0.567 Z_{t-1} \qquad (3)$$

The fitted ARIMA (1, 0, 1) for female data can be described as:

$$X_t = \phi_1 X_{t-1} + Z_t + \theta_1 Z_{t-1}$$
$$X_t = 919.84 \;\; + 0.746 X_{t-1} - 0.566 Z_{t-1}$$

The fitted ARIMA (1, 1, 1) for peads data can be described as:

$$W_t = \phi_1 W_{t-1} + Z_t + \theta_1 Z_{t-1}$$
$$W_t = -2.422 + 0.455 W_{t-1} - 0.107 Z_{t-1} \qquad (5)$$

FORECASTING

Three months forecasting of male, female and peads patient's is estimated on the basis of best selected model is shown in table-VIII.

Month	Male		Female		Peads	
	Esti-mated	Actual	Esti-mated	Actual	Esti-mated	Actual
Jan 2014	632	649	889	874	119	102
Feb 2014	626	599	886	812	118	98
March 2014	623	675	883	980	117	110

Table–VIII. The estimated and actual number of patients

CONCLUSION

A best model for Male, Female, and Peads patient's data is developed for forecasting on the basis of available tools. The empirical analysis indicated that ARIMA(1,0,1) is best fitted model for male and female patients data and ARIMA(1,1,1) for peads for short run forecasting. The estimated number of patients for next three months is given in Table No. 8 and compare with actual data.

The finding of this study may be useful for future planning, clinical researchers, hospital administration, and Government also for the welfare and betterment of patients and health care staff.

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ETHICAL CONSIDERATION

This study was carried out on the patient's data available at OPDCL records and there was no direct interaction with patient, no patients personal identification was used, so the study has not reviewed by Institutional Review Board (IRB).

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"He who wishes to be obeyed must know how to command."

Niccolo Machiavelli

AUTHORSHIP AND CONTRIBUTION DECLARATION

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3	Abdul Majeed Akhtar	Literature review	
4	Zaheer-ul-Hassan Mir	Theme of study	
5	Safoora Akbar	Overall management	
6	Maqsood Ahmad	Writing the paper	