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Selecting Best Arima Model for Poison Data at Different Parameter Values

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Abstract

A problem occurs when poison data have to be modeled. The number of counts in a certain period can only be an integer that is why the commonly used Autoregressive Moving Average (ARMA) model in time series, which assumes stationarity, seems not very useful anymore, simply because there are some associated problems like outlier and over dispersion that can be encountered in the poison data. For this problem, Integrated Autoregressive Moving Average (ARIMA) models were studied. These models were used to capture poison data with different phenomena. Data set were simulated from poison process with $\lambda = 5, 10$ and 20. ARIMA (p, q) were then fitted to the simulated data so as to examine the effect of the changes in parameter value of the poison on the models$'$ performance across the sample size. It was concluded that ARIMA (2,1,2) and ARIMA (1,1,2) are obviously the best at lower and higher sample sizes respectively.

1. Introduction

Time series data involving counts are frequently follows a poison distribution. This can be encountered in many biomedical and public health applications. For example, in disease surveillance, the occurrence of rare infections over time is often monitored by public health officials for the purpose of monitoring changes in disease activity. The primary objective of time series modeling is to study techniques and measures; for drawing inferences from past data. The models can be employed to describe and analyze the sample data and make forecasts for the future. The main advantage of time series models is that they can handle any persistence patterns in data [1].

For time series, certain models are commonly known, like an Autoregressive Moving Average (ARMA) model. This method takes into account that past information influences the variables of today. For example, the rate of inflation of a few days ago influences the

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rate of inflation today. Or import and export data can be predicted by using information on how many is imported and exported in the past few months. Many examples can be given and these ARMA-models work pretty well in modeling the time series [2].
One special class of time series model is Integrated Autoregressive Moving Average (ARIMA) which are often associated with [4]. Effort to systematize the whole methodology of estimating, checking and forecasting using ARIMA models are discussed by [5]. The Box-Jenkins method consist of three steps: identification, parameter estimation and forecasting. Among these three steps, the identification step, which involves order determination of the AR and MA part of ARIMA model, is important. This step requires statistical information such as the autocorrelation and partial autocorrelation [4]. The problem of estimating the order and the parameters of an ARMA model is still an active area of research. The Box and Jenkins Variant of the ARIMA model is predestinated for applications to non-stationary after differencing.
Among the most effective approaches for analyzing time series data is the model introduced by Box and Jenkins, (ARIMA). In a study [10] used Box-Jenkins methodology to build ARIMA model for monthly rainfall data taken for Amman airport station for the period from 1922-1999 with a total of 936 readings. In their research, [(0, 1, 1).sup.12] model was developed. This model was used to forecasting the monthly rainfall for the upcoming years to help decision makers establish priorities in terms of water demand management. They then recommended an intervention time series analysis to be used to forecast the peak values of rainfall data. [11] presented three ARIMA models which used macroeconomic indicators to model the USD/EUR exchange rate. They discovered that over the time period from January 1994 to October 2007, the monthly USD/EUR exchange rate was best modeled by a linear relationship between its preceding three values and the current value. These authors concluded that ARIMA (1,1,1) is the most suitable model for the prediction of time series of USD/EUR exchange rate. [10], applied Box-Jenkins methodology for ARIMA model to exchange rate (Naira to Dollar) within the periods 1982-2011 and it was proved that, the best fit is ARCI) model, because it has the most suitable AIC, this was achieved through the diagnostic checking which identified it as the best fit.
[6] used Box-Jenkins models to investigate the behaviour of daily exchange rates of the Romanian Leu against Euro, United states Dollar, British Pound, Japanese Yen, Chinese Renminbi and the Russian Ruble using exponential smoothing techniques and ARIMA models. The results indicated that exponential smoothing techniques in some cases outperform the ARIMA models. Hillmer and Tiao used ARIMA technique for the seasonal adjustment as well as introduce the decomposition of the time series data into its mechanism like trend, seasonal and noise whereas such series will follow the assumption of the Gaussian ARIMA model.
[3] studied the impact of the size of the historical data on ARIMA models in formulating accuracy. The study used 286 weekly records of amount of solid waste generated in Arusha city to formulate four (4) ARIMA models suing different data lengths or size. The first model, M_1 used 30 observations the second model, M_2 used 60 observations, the third model, M_3 used 120 observations and the fourth mode M_4 used 260 observations of which are the most recent. A total of 26 observations were held out for validation. The precision in forecasting was tested using MAPE, RMSE and MAD. The results indicated variation in precision , M_3 performed best in one-week ahead and 9-12 weeks ahead while M4 did best in 2-8 weeks and also for 13 weeks and above, M_1 was the worst mode in forecasting.
[7] examined empirically the best ARIMA model for forecasting average daily share price indices of the series of square pharmaceuticals limited (SPL). After stationary test, the

data was found to be not stationary, a differencing was carried out to obtain stationarity. The results indicated that the best ARIMA model was found to be ARIMA (2,1,2).
Other empirical analysis has been addressed by modelling a time series of count data (see [8], [9] and [12]), in the area of accident prevention, epidemiology and monthly cases of polio respectively. However, most of them did not take cognizant of a particular distribution say poison distribution and effect of sample size on different parameter of poison data. Most of these applications involve relatively rare events which makes the use of the normal distribution questionable. Thus, modelling this type of series requires one to choose the best model that can deal explicitly with the problem of the non-stationarity and non-normality. These problems were therefore addressed by using Integrated Autoregressive Moving Average (ARIMA) on different parameter (mean) of poison generated data which has not been addressed in the literature. The orders of the models were studied in respect to the level of sample sizes through Mort-Carlo simulation. The objective of this study is to investigate the best ARIMA model that can describe the poison data at different parameter values.

2. Materials and Methods

Data set were simulated in R statistical software with sample sizes of 20, 40, $\cdots$, 200 from poison process of $\lambda_i,\ i = 5,\ 10\ 15$ and 20. The four models under study, namely: ARIMA (1,d,1), ARIMA (1,d,2), ARIMA (2,d,1) and ARIMA (2,d,2) were then be fitted to the simulated data so as to examine the effect of the proportion of changes in mean and sample size on them. Their performance was compared at different sample sizes and means of poison. Thereafter, the forecast performances of the four fitted models were also be examined at different steps ahead. All cases of simulation will be randomized and replicated 1000 times each for the respective selected sample sizes.
In simulation, we set our parameters to be $\emptyset_1 = 1$ and $\emptyset_2 = 1$, to ensure discrete nature of poison data generated. The response Y_{ti} in 3.1 will generated from poison distributions. The four models under study will be considered to analyse how well each of the model fits the selected data sets. Data were generated from linear second orders of autoregressive functions given as follows:

$$Model1.AR(2) : Y_{ti} = Y_{ti-1} + Y_{ti-2} + e_t \tag{2.1}$$

$$t = 10,\ 20,\ 30,\ 40,\ 50,\ 60,\ 70,\ 80,\ 90,\ 100\ i = 1, 2, \cdots,\ 1000$$

where Y_{ti} will be simulated from poison as follows:
The Poisson regression model which is based on the Poisson distribution with probability density function

$$\frac{\lambda^{y_i} e^{-\lambda_i}}{y_i!},\ for y_i = 0, 1, 2, \cdots \tag{2.2}$$

Thus, for the Poisson models $E\left(y_i\right) = V\left(y_i\right) = \mu_i$.

2.1. **Test stationarity of time series data.** To model the series, we check the structure of the data in order to obtain some preliminary knowledge about the stationarity of the series, whether there exist a trend or seasonal pattern. A time series is said to be stationary if both the mean and variance are constant over time. If the data is non-stationary, we do a logarithmic transformation or take the first order difference of the data series which may lead to a stationary time series. This process will be repeated until the data exhibit no apparent deviations from stationarity. The times of differencing of the data is indicated

by the parameter d in the ARIMA (p,d,q) model. Then an Augmented Dickey fuller test (ADF) test is used to determine the stationarity of the data.
The testing procedure for the ADF test is the same as for the Dickey-Fuller test but it is applied to the model. A random walk with drift and trend is represented as:

$$\Delta Y_t = \alpha + \beta_t + \Upsilon Y_{t-1} + \sigma_1 \Delta Y_{t-1} + \cdots + \sigma_{p-1} \Delta Y_{t-p+1} + \varepsilon_t \tag{2.3}$$

where α is a constant, β the coefficient on a time trend and p is the lag order of the autoregressive process. Imposing the constraints $\alpha = 0$ and $\beta = 0$ corresponds to modelling a random walk and using the walk with a drift.
The test statistic, value is calculated as follows:

$$t = \frac{\hat{\Upsilon}}{\sigma \hat{\Upsilon}} \tag{2.4}$$

where $\hat{\Upsilon}$ is the estimated coefficient and $\sigma\hat{\Upsilon}$ is the standard error in the coefficient estimate.
The null-hypothesis for an ADF test: $H_0 : \Upsilon = 0 Vs H_1 : \Upsilon < 0$
where H_0: is the null hypothesis (has unit root) and H_1: Does not have unit root. The test statistics value t is compared to the relevant critical value for the Dickey-Fuller test. If the test statistic is less than the critical value, we reject the null hypothesis and conclude that no unit-root is present. The ADF test does not directly test for stationarity but indirectly through the existence (or absence) of a unit-root.
Decision rule:
If t> ADF critical value = reject null hypothesis, that is, unit root exists.
If t< ADF critical value = not reject null hypothesis, that is, unit root does not exist.
Using the usual 5% threshold, differencing is required if the p – value is greater than 0.05.

3. Simulation Results and Data Analysis

The results of the ARIMA models [ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (2,1,1) and ARIMA (2,1,2)] presented are Tables 1-12. In the first instance, model identification were carried out and test of stationarity were tested are presented in table 1-3. Furthermore, the data simulated were differenced. The experiment was repeated 1000 times for the four models and each sample size.

Table 1: ADF Test on Poison Data with $\lambda = 5$ at different Sample Sizes

Sample Size	Values	Lag order	P-value	Hypothesis (H_o)	Decision	Remark
20	-3.0077	2	0.1885	Unit root	Accept H_o	Not stationary
40	-2.2075	3	0.492	Unit root	Accept H_o	Not stationary
60	-2.8784	3	0.2197	Unit root	Accept H_o	Not stationary
80	-3.715	4	0.02884	Unit root	Reject H_o	Stationary
100	-5.2466	4	<0.01	Unit root	Reject H_o	Stationary
120	-4.398	4	<0.01	Unit root	Reject H_o	Stationary
140	-4.7182	5	<0.01	Unit root	Reject H_o	Stationary
160	-4.6407	5	<0.01	Unit root	Reject H_o	Stationary
180	-5.8542	5	<0.01	Unit root	Reject H_o	Stationary
200	-5.2129,	5	<0.01	Unit root	Reject H_o	Stationary

Table 1 above shows ADF has the p-values which are greater than the critical value of 0.05 for lower sample sizes and we accept null hypothesis of having unit root series for the series. However, as sample size increases, the data series is stationary due to the p-values less than 5%. It clear that the time series plot of the poison data series and stationarity tests suggest that the data need to be transformed or differenced since it is confirmed to have a unit root at lower sample sizes.

Table 2: ADF Test of Differenced Poison Data with $\lambda = 5$ at different Sample Sizes

Sample Size	Values	Lag order	P-value	Hypothesis (H_o)	Decision	Remark
20	-2.8068	2	0.025	Unit root	Reject H_o	Stationary
40	-3.0384,	3	0.016	Unit root	Reject H_o	Stationary
60	-4.3813	3	<0.01	Unit root	Reject H_o	Stationary
80	-3.8288	3	0.023	Unit root	Reject H_o	Stationary
100	-4.9996	4	<0.01	Unit root	Reject H_o	Stationary
120	-4.5907,	4	<0.01	Unit root	Reject H_o	Stationary
140	-3.9346	4	0.014	Unit root	Reject H_o	Stationary
160	-4.157	5	<0.01	Unit root	Reject H_o	Stationary
180	-3.8714	5	0.0173	Unit root	Reject H_o	Stationary
200	-5.565	5	<0.01	Unit root	Reject H_o	Stationary

Table 2 presents the stationarity tests for the differenced poison data with parameter λ=5 over the period of investigation with a null hypothesis of a unit root against alternative hypothesis of a level of stationarity. The p-values of 0.01 are less than the 5% level of significance while p-value which indicate that, the null hypothesis of having a unit root series should be rejected in favour of alternative of being stationary. Indeed, the data is stationary after the first difference hence we can proceed to fitting and forecasting of the series.

3.1. **Performance of ARIMA (p,1,q) Models on Poison Data with Parameter ($\boldsymbol{\lambda} = 5$).** Table 3 below gives the relative performance of the ARIMA (p,1,,q) with parameter $\lambda = 5$ at different sample sizes based on the AIC and BIC criteria . The results were plotted on figures 1a and 1b.

Table 3 AIC and BIC Values of ARIMA (p,1,q) of with Parameter ($\lambda = 5$)

Criteria	AIC				BIC			
Sample Sizes	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,1)	ARIMA (2,1,2)	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,1)	ARIMA (2,1,2)
20	98.048	99.4584	94.4932	91.259	100.720	103.019	98.0547	95.712
40	208.108	196.034	190.555	189.614	213.021	202.584	197.106	197.801
60	311.713	298.668	303.529	283.811	317.894	306.91	311.771	294.114
80	370.996	366.734	396.660	385.635	378.066	376.161	406.087	397.419
100	497.755	467.567	446.083	452.469	505.510	477.907	456.422	465.393
120	599.586	546.161	572.275	571.993	607.898	557.244	583.358	585.846
140	706.667	714.975	686.157	631.34	715.449	727.225	697.866	645.976
160	755.901	762.409	779.56	727.905	765.088	774.66	791.811	743.218
180	892.128	776.746	845.144	800.759	901.673	894.73	857.871	816.668
200	979.827	863.746	933.499	908.944	989.692	876.899	946.652	925.385

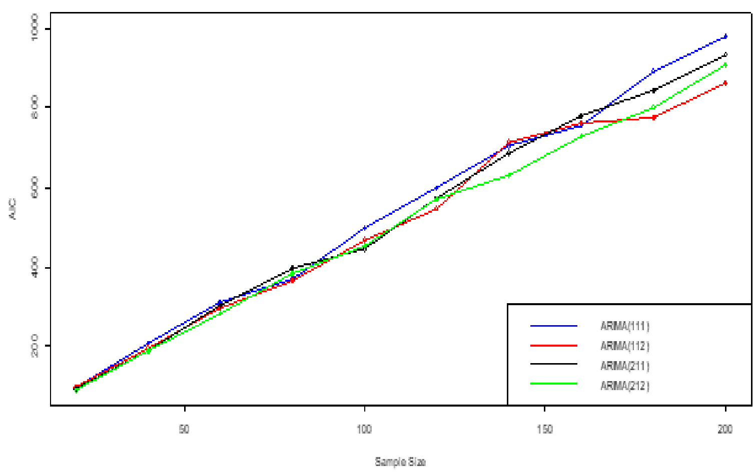

Figure 1a: AIC values of the Fitted models on Poison Data with Parameter $\lambda = 5$

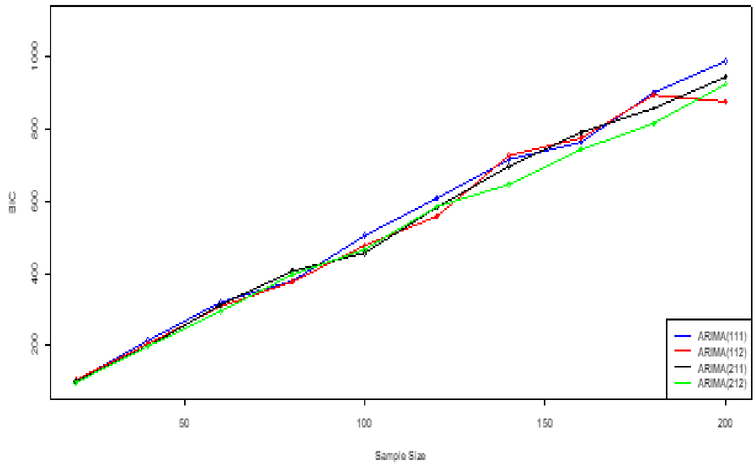

Figure 1b: BIC values of the Fitted models on Poison Data with Parameter $\lambda = 5$

Table 3 shows the fitted performances of the four ARIMA model to data simulated with underline poison distribution of parameter with the average values of AICs and BICs of each model at various sample sizes. The results obtained were plotted on the graphs as shown in Figure 1a and 1b respectively. The best fitted model based on AIC and BIC criteria is ARIMA (2,1,2) followed by ARIMA (1,1,2), especially, at lower sample sizes below 180 while ARIMA (**??**) is the best from sample size of 180 and above. ARIMA (1,1,1) is the worst among fitted models across the periods and sample sizes.

Table 4: ADF Test on Poison Data with $\lambda = 10$ at different Sample Sizes

Sample Size	Values	Lag order	P-value	Hypothesis (H_o)	Decision	Remark
20	-3.6268	2	0.04808	Unit root	Reject H_o	Stationary
40	-4.2136	3	0.01146	Unit root	Reject H_o	Stationary
60	-6.1385	3	<0.01	Unit root	Reject H_o	Stationary
80	-5.4582	4	<0.01	Unit root	Reject H_o	Stationary
100	-3.3743	4	0.06277	Unit root	Reject H_o	Stationary
120	-5.1814	4	<0.01	Unit root	Reject H_o	Stationary
140	-5.0753	5	<0.01	Unit root	Reject H_o	Stationary
160	-4.7945	5	<0.01	Unit root	Reject H_o	Stationary
180	-5.593	5	<0.01	Unit root	Reject H_o	Stationary
200	-5.7945	5	<0.01	Unit root	Reject H_o	Stationary

3.2. **Performance of ARIMA (p,1,q) Models on Poison Data with Parameter ($\boldsymbol{\lambda} = 10$).** Table 5 below gives the relative performance of the ARIMA (p,1,,q) with parameter $\lambda = 10$ at different sample sizes based on the AIC and BIC criteria . The results were plotted on Figures 2a and 2b.

Table 5 AIC and BIC Values of ARIMA (p,1,q) ofwith Parameter ($\lambda = 10$)

Criteria	AIC				BIC			
Sample Sizes	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,1)	ARIMA (2,1,2)	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,1)	ARIMA (2,1,2)
20	109.565	104.758	112.444	101.450	112.398	108.535	116.222	106.172
40	208.222	212.151	216.951	207.460	213.212	218.806	223.606	215.778
60	314.531	312.488	308.334	330.441	320.763	320.798	316.644	340.828
80	408.571	413.369	413.822	411.615	415.679	422.847	423.300	423.463
100	507.671	524.302	515.869	543.901	515.456	534.682	526.249	556.876
120	597.063	596.940	607.364	630.043	605.400	608.057	618.480	643.939
140	704.063	707.108	733.050	701.437	712.866	718.846	744.788	716.109
160	807.426	816.501	853.909	834.713	816.633	828.776	866.185	850.057
180	927.558	921.701	897.163	927.493	937.121	934.451	909.912	943.430
200	1034.70	1071.11	1052.56	1049.32	1044.58	1084.28	1065.73	1065.79

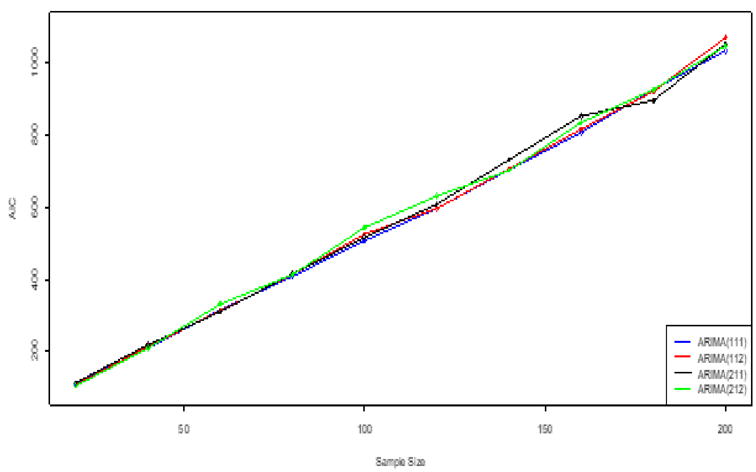

Figure 2a: AIC values of the Fitted models on Poison Data with Parameter $\lambda = 10$

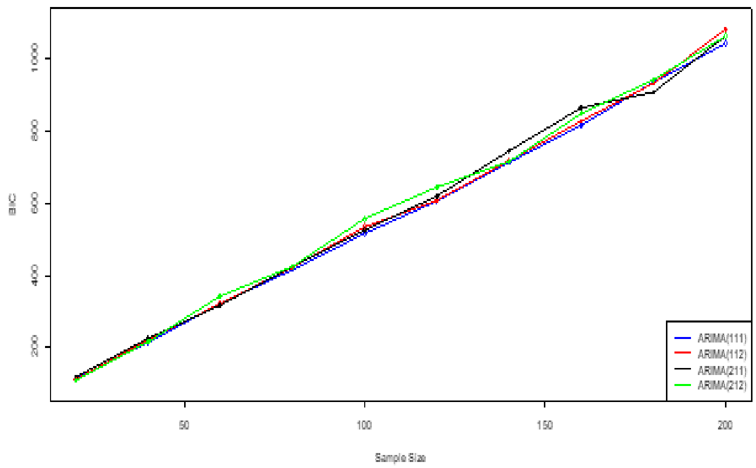

Figure 2b: BIC values of the Fitted models on Poison Data with Parameter $\lambda = 10$

Table 5 shows relative performance of the four fitted ARIMA models with the average values of AIC and BIC of each model at various sample sizes. The results obtained were plotted on the graphs as shown in Figure 2a and 2b respectively. The best fitted model on poison data with parameter $\lambda = 10$ is ARIMA (**??**), especially at various sample sizes followed by ARIMA (2,1,2). ARIMA (2,1,2) out performed others as sample sizes increases based on AIC criteria.

Table 6: ADF Test of Poison Data with $\lambda = 20$ at different Sample Sizes

Sample Size	Values	Lag order	P-value	Hypothesis (H_o)	Decision	Remark
20	-2.8515	2	0.248	Unit root	Reject H_o	Stationary
40	-3.946	3	0.02188	Unit root	Reject H_o	Stationary
60	-3.0749	3	0.1403	Unit root	Reject H_o	Stationary
80	-3.8491	4	0.02088	Unit root	Reject H_o	Stationary
100	-4.333	4	<0.01	Unit root	Reject H_o	Stationary
120	-4.4322	4	<0.01	Unit root	Reject H_o	Stationary
140	-4.9275	5	<0.01	Unit root	Reject H_o	Stationary
160	-5.6941	5	<0.01	Unit root	Reject H_o	Stationary
180	-5.8183	5	<0.01	Unit root	Reject H_o	Stationary
200	-5.8718	5	<0.01	Unit root	Reject H_o	Stationary

3.3. **Performance of ARIMA (p,1,q) Models on Poison Data with Parameter ($\boldsymbol{\lambda} = 20$).** Table 6 below gives the relative performance of the ARIMA (p,1,,q) with parameter$\lambda = 20$ at different sample sizes based on the AIC and BIC criteria . The results were plotted on figure 3a and 3b.

Table 7 AIC and BIC Values of ARIMA (p,1,q) ofwith Parameter ($\lambda = 20$)

Sample Sizes	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,1)	ARIMA (2,1,2)	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,1)	ARIMA (2,1,2)
20	121.293	131.669	120.510	120.556	124.127	135.447	124.288	126.278
40	248.819	239.329	244.383	235.889	253.809	245.983	251.037	254.207
60	341.452	345.023	342.613	339.917	347.684	353.333	350.924	350.305
80	495.409	491.951	483.401	443.677	502.517	501.429	492.878	455.524
100	572.069	599.048	591.894	576.839	579.854	609.428	602.275	589.814
120	687.362	695.285	692.641	698.687	695.699	706.401	703.758	712.582
140	797.261	828.101	835.319	806.991	806.065	839.838	847.057	821.663
160	945.708	933.620	912.399	953.358	954.915	945.896	924.675	968.702
180	1059.77	1050.19	1078.32	1091.31	1069.34	1062.94	1091.07	1107.25
200	1159.28	1142.56	1194.43	1188.49	1169.16	1155.74	1207.60	1204.96

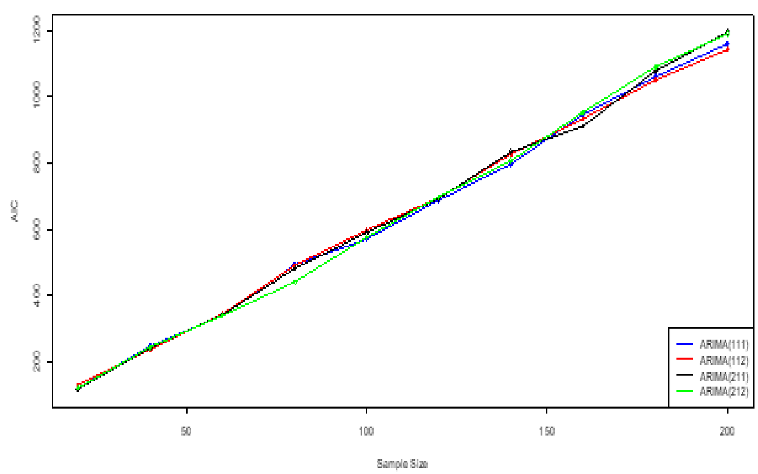

Figure 3a: AIC values of the Fitted models on Poison Data with Parameter $\lambda = 20$

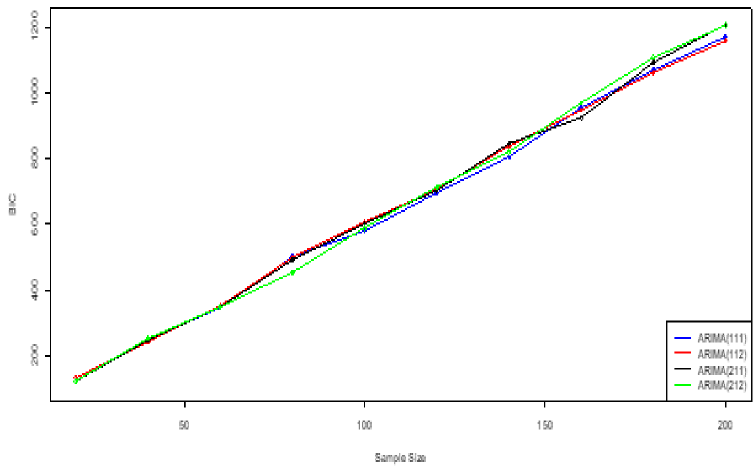

Figure 3b: BIC values of the Fitted models on Poison Data with Parameter $\lambda = 20$

Table 7 shows the fitted performances of the four ARIMA models to data simulated under poison data with $\lambda = 20$. The average values of AIC and BIC of each model at various sample sizes recorded. The results obtained were plotted on the graphs as shown in Figure 3a and 3b respectively From Figure 3a and 3b; the four models have close performances on the basis of AIC and BIC. However, it can be seen that the ARIMA (2,1,2) model performs more absolutely well than other models at sample sizes below 150 while ARIMA (1,1,2) performs best at higher sample sizes due to their lowest value of AIC. However, the performance of the ARIMA (1,1,1) models supersedes others at the moderate sample size of 150.

3.4. **Relative Forecast Performance of the Models When Sample Size is small with $\boldsymbol{\lambda = 5}$.** In this section, data were simulated under the condition of the poison with $\lambda = 5$, and then fitted to ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (2,1,1) and ARIMA (2,1,2) models which are the best models under this category. Thereafter, the fitted models were used to predict h-steps ahead based on the observations using small sample size of 20. The Theil U Statistic computed from 1000 iterations from each model at different of steps ahead were recorded below.

Table 8 Forecast Performance of the Models using Theil U Statistic

Steps Ahead	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,1)	ARIMA (2,1,2)
5	1.33013	2.84114	2.57219	3.1075
10	1.30324	2.81424	2.54529	3.09641
15	0.27634	2.78735	2.5184	3.0435
20	0.24944	2.76045	1.4915	3.0286
25	0.22255	2.73356	1.46461	3.0026
30	0.19565	2.70666	1.43771	2.9785
35	0.16876	2.67977	1.41082	2.94872
40	0.14186	2.65287	1.38392	2.92182
45	0.11497	2.62598	1.35703	2.89493
50	0.08807	2.59908	1.33013	2.86803

Based on the Theils Analysis in table 8 above, the ARIMA (2,1,2) has the highest forecasting power due to their values greater than 1 and also greater than other values of the models across the steps ahead; this is followed by ARIMA (1,1,2) and ARIMA (1,1,1). However, the Theil values of ARIMA (2,1,1), at higher steps ahead are close to zero, hence it is not as good as other models in forecasting. Indeed, the forecasting ability of all the models decrease as steps ahead increase.

Recommendations: Based on the above results, the following recommendations were made:

(1) The ARIMA (2,1,2) and ARIMA (1,1,2) models are recommended in capturing poison data with parameter λ =5, λ =10 and λ =20.
(2) In further research, the above models can be applied on other data, as well as comparing the comparing with other models
(3) Extension of these models or other models to compare with can also be area of interest.

Conclusions: In this study, comparative performance of the ARIMA models of different orders was carried out on foreign exchange data. It can be seen that, because of the volatile nature of the data. In the comparative performances of the models ARIMA (2,1,2) models are obviously preferred to be the best model that captured the poison data with different parameter at lower sample sizes using the selected criteria while ARIMA (1,1,2) is chosen as the best for the data with higher sample sizes. However, the best performance of all the fitted models are experienced at lower sample sizes. Based on the forecasting ability of the models, the ARIMA (2,1,2) has the highest forecasting power due to their values greater than 1 and also greater than other values of the models across the steps ahead; this is followed by ARIMA (1,1,2) and ARIMA (1,1,1). However, the Theil values of ARIMA (2,1,1), at higher steps ahead are close to zero, hence it is not as good as other models in forecasting. Indeed, the forecasting ability of all the models decrease as steps ahead increase.

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References

[1] Abdullahi, S. K. & Tayfur, A. (2004). An experimental study on Forecasting using test processes. *Proceeding of Water Simulation Conference, R.G ingalls, M. D. Rossetti, J. S. Smith, and B.A Peters, eds.* 437-442.

[2] Akeyede I., Adeleke B. L. & Yahya W. B. (2016). Linear and Nonlinear Time Series Model Selection for Stationary Data Structure: Application to Monthly Rainfall Data in Nigeria. *ASUU Journal of Science.* **21**, 1-13.

[3] Amon M., Dimitry K. & Silas M. (2015). Analyzing the impact of historical data length in non-seasonal ARIMA models Forecasting. *Mathematical Theory and Modelling.* **5** (10), 77-85.

[4] Box G. E. P. & Jenkins G. M. (1976). *Time series Analysis Forecasting and Control.* Holden-Day Inc., San Francisco.

[5] Brannas K. & Per J. (2016). Time series count data regression. *Communications in Statistics: Theory and Methods.* **23**, 2907-2925.

[6] Fat C. M. & Dezei E. (2011). *Exchange-rates Forecasting: exponential smoothing techniques and Arima Models [Online]* Faculty of Economics and Business Administration, Department of Finance, Babes-Bolyai Universit, Cluj- Napoca Romania, Retrieved From http://steconomiceuradea.Ro/anale/volume/2011/N/046, Pdf.

[7] Jiban Chandra Paul, Ms. Shahidul Hoque & Mohammed Morshedur Rahman (2013). Selection of Best ARIMA Model for Forecasting Average Daily Share Price Index of Pharmaceutical Companies in Bangladesh, Global Journal of Management and business Research Finance, Publisher. *Global Journal Inc (U.S.A) Online.* **13** (1.0), 123-132.

[8] Johansson P. (1996), Speed limitation and motorway casualties: a time series count data regression approach. *Accident Analysis and Prevention.* **28**, 73-87.

[9] Magnus F. J. & Fosu O. (2020). Modelling and Forecasting volatility of on Returns in the Ghana stock Exchange using GARCH models. *Journal of Applied Sci..* **3**, 2042-2048.

[10] Nwankwo S. C. (2014). Autoregressive Integrated Moving Average (ARIMA) Model for exchange Rate (Naira to Dollar). *Academic Journal of Interdisciplinary Studies, MCSER Publishing, Rome-Italy* **3** (4), 429-433.

[11] Weisang G. & Yukika A. (2008). *Vagaries of Euro: an Introduction to ARIMA Modelling, [Online].* Bentley College USA, Retrieved from http://www.bentley.edu.centers/files/csbigs/weisang,pdf.

[12] Zeger S. L. (1988). A regression model for time series of counts. *Biometrika.***75**, 621-629.