



A MONTE CARLO STUDY ON THE PERFORMANCE OF EMPIRICAL THRESHOLD AUTOREGRESSIVE MODELS UNDER VIOLATION OF STATIONARITY ASSUMPTIONS

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ABSTRACT

One of the major importance of modeling in time series is to forecast the future values of that series. And this requires the use of appropriate method to fit the time series data which are dependent on the nature of the data. We are aware that most financial and economic data are mostly non-stationary. . The study is an extension of the work of Romsen et al (2020) which dealt with forecasting of nonlinear data that are stationary with only two threshold regimes. The study recommendations that In further research, the above models can be extended to other regimes (such as the 3 – regimes Threshold models) as well as comparing them with other regimes to understand the behaviors of the other regimes in selecting a suitable model for a data. STAR (2,1) and SETAR (2,2) are recommended to fit and forecast nonlinear data of trigonometric, exponential and polynomial forms respectively that are non-stationary.

Keywords: Stationarity, Exponential, Regimes, Auto regressive

INTRODUCTION

A time series forecasting is the use of model to predict the future values based on the past values. Predictions were made when the actual outcome of event(s) may not be known until in some future time. The goal of time series is to forecast and identify meaningful characteristics in data that can be used in making statements about the future outcomes. Time series are generally classified into stationary and non-stationary. A stationary time series has its statistical properties such as the mean, variance, auto covariance's, auto correlation etc. are all constant over time. Since its characteristics are constant, then a stationary time series can be easily predicted because all its statistical properties that were constant in the past will for likely be constant at the future. On the other hand, a non-stationary time series is the one whose statistical properties change over time. And this need to be further converted into stationary data because using non-stationary time series especially in financial models produces unreliable result and leads to poor understanding and forecasting.

Related literatures

The most commonly used linear time series models are Auto regressive (AR), moving average (MA), Auto regressive moving average (ARMA) and the Auto regressive integrated moving average (ARIMA) models. Autoregressive (AR) process is a model in which future values are forecast purely on the basis of past values of the time series. Moving average (MA) process is a model in which future values are forecast purely on the basis of past shocks (or noise or random disturbances). A model that uses both past values of the time series and past shocks is called an autoregressive-moving average (ARMA) process. And lastly, the ARMA model of a differenced series is called an ARIMA model. 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 word "Integrated". The three models (AR, MA and ARMA) assumes that the time series is stationary, that is its statistical properties are all constant over time. As stated earlier that most time series problems are known to be non-stationary and there is need to be transformed to achieve stationarity. Differencing is usually needed to be employed, hence an ARMA model of a differenced series is called an ARIMA model. Where the

word Integrated was included in order to obtain an output needs to be anti-differenced or integrated, to forecast the original series.

Makridaki&Insead (1997) aims to apply the Box-Jenkins methodology to ARIMA models and determine the reasons why in empirical tests in the post-sample forecasting the accuracy of such models is generally worse than much simpler time series methods. The paper concludes that the major problem is the way of making the series stationary in its mean (i.e. the method of differencing) that has been proposed by Box and Jenkins. The result also shows that using ARMA models to seasonally adjusted data slightly improves post-sample accuracies while simplifying the use of ARMA models. The result also confirmed that transformations slightly improve post-sample forecasting accuracy, particularly for long forecasting horizons. And finally the result demonstrated that AR(1), AR(2) and ARMA(1,1) models can produce more accurate post-sample forecasts than those found through the application of Box-Jenkins methodology.

Guidolin et. al (2019) examines the comparative predictive performances of a number of linear and non-linear models for stock and bond returns in the G7 economies. Non-linear models appear to forecast better in the case of US and UK asset returns, whereas simple linear models (such as the random walk and univariate autoregressions) appear to forecast better in the case of French, Italian and German asset returns.

MATERIALS AND METHODS

Estimation of Parameter to be Fixed for Simulation Model
From the pth order of autoregressive [AR (p)], the first order AR (1) and second order AR (2) were deduced

$$AR (1): X_t = \alpha X_{t-1} + e_t \quad (1)$$

$$\sigma_e^2 = \frac{\sigma_e^2}{1-\alpha^2} \quad (2)$$

$$AR (2): X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + e_t \quad (3)$$

$$\sigma_e^2 = \frac{\sigma_e^2}{1-\alpha_1^2-\alpha_2^2} \quad (4)$$

The specified parameter values were estimated by fixing $\sigma_e^2 = 2$, $\sigma_t^2 = 4$ and $\alpha_1 = 0.7$, to be $\alpha_2 = 0.6$. This imply that the simulation was simulated using these

parameters estimated will have a unit root and hence non-stationary

Models Selected for Simulation

The simulation Data is generated from several linear and nonlinear second orders of general classes of autoregressive functions given as follows:

Model 1. AR(2): $X_{ti} = 0.7X_{ti-1} - 0.6X_{ti-2} + e_t$, (5)
 $t = 1, 2, \dots, 20, 40, 60, 80, 100, 120, 140, 160, 180, \text{ and } 200.$
 $i = 1, 2, \dots, 1000$

The following codes were written to simulate data of sample size 20 from model 1 above

```
e1 <- rnorm(20,1,2)
x1 <- rnorm(20,2,4)
for (t in 3:20)x[t] <- 0.7 * x[t - 1] - 0.6 * x[t - 2] +
e[t] - - (6)
```

Up to the model 4 which is

Model 4: PL(2): $X_{ti} = 0.7X_{ti-1}^2 - 0.6X_{ti-2} + e_t$, (7)

Test of Linearity/ Nonlinearity

Two tests of nonlinearity were used to confirm the nonlinear data generated, these are Keenan and Tsay F tests. Both statistics test null hypothesis that data series is nonlinear. The procedure for each statistic are stated as follows

Keenan’s One-Degree Test for Nonlinearity

The Keenan Test examines and tests the Quadratic Nonlinearity Hypothesis and provides information on threshold nonlinearity. This situation refers to the F test in the following model:

$$X_t = \mu + \sum_{u=-\infty}^{\infty} a_u \varepsilon_{t-u} + \sum_{u,v=-\infty}^{\infty} a_{u,v} \varepsilon_{t-u} \varepsilon_{t-v} \tag{8}$$

Tsay’s Test for Nonlinearity

Tsay’s (Tsay, 1986) linearity test is based on recursive auto regression and destructive term estimators, and firstly, the recursive auto regressions are established starting from b . is expressed as $b=(n/10) + p$ observation value in return for the p and the relevant d values with AR level, and then the model is established between \hat{e}_t values and $(1, X_{t-1}, X_{t-2}, \dots, X_{t-p})$. Then the following test is obtained among the inclusions of the model formed with \hat{e}_t

$$\hat{F}(p, d) = \frac{[\sum \hat{e}_t^2 - \sum \hat{e}_t^2]/(p+1)}{\sum \hat{e}_t^2 / (n-d-b-p-h)} \tag{9}$$

Estimation of SETAR Models

Estimation of SETAR models is often carried out by the nonlinear least squares method. Properties of the resulting estimators are hard to establish, however. As a matter of fact, limiting properties of the least squares estimates are only available for the two-regime SETAR(p) model. It is believed that similar results can be shown for multi-regime SETAR models. Chan (1993) considered the estimation of the two-regime SETAR(p) model of Equation (9). Let $\phi = (\phi_0, \phi_1, \dots, \phi_p)'$ and $\theta = (\theta_0, \theta_1, \dots, \theta_p)'$ be the parameter vectors of the two regimes, respectively. Let $\Theta = (\phi', \theta, r, d)'$ be the coefficient vector of the model in Equation (9) and Θ_0 be the true coefficient vector. Suppose that the realizations $\{X_1, \dots, X_T\}$ are available, where T denotes the sample size.

Smooth transition Autoregressive (STAR) model

Another class of nonlinear time series models is smooth transition autoregressive (STAR) models. The STAR model is similar to the self-exciting threshold autoregressive model. The main difference between these two models is the mechanism governing the transition between regimes. A two-regime model will be considered here. The concept can be extended to the case with more than two regimes.

Evaluation and Comparison of the Models

Simulation studies were conducted to investigate the performances of Autoregressive (AR), Self- Exciting Threshold autoregressive (SETAR), Smooth Transition Autoregressive Models (STAR) in fitting and forecasting linear, trigonometric, exponential and polynomial forms of autoregressive time series under study (model 1-4). Effect of sample size and the stationarity of the models were examined on each of the general linear and nonlinear data simulated.

Criteria for Assessment of the Study

The goodness of fit for each model was assessed using three common information criteria (AIC, MAPE and MSE) in time series. The model with lowest criteria is the best among the models.

Akaike Information Criteria

There are several information criteria available to determine the best model of autoregressive process. All of them are likelihood based; the well-known is Akaike information criterion (AIC).

RESULTS AND DISCUSSION

Table 1: MSE of SETAR and STAR Models across Sample Sizes Fitted on AR (2): $X_{ti} = 0.7X_{ti-1} - 0.6X_{ti-2} + e_t$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	3.4916	3.3893	4.8638	4.1091	4.4153	3.5648
40	3.9660	3.7852	5.8296	4.1983	4.1402	4.1849
60	4.0522	4.0157	5.3391	4.9072	4.9424	4.8346
80	3.9358	4.1073	5.0705	4.6135	4.6693	4.6003
100	3.9329	4.0630	5.1909	4.1576	4.2277	4.1639
120	3.7256	3.8715	5.0806	4.0375	4.0628	4.1595
140	3.7219	3.7614	4.5859	3.9492	3.9252	4.0130
160	3.7069	3.6009	4.0380	3.9196	3.9352	3.9730
180	3.7286	3.5142	3.9421	3.9159	3.9050	3.9380
200	3.5581	3.1785	3.9928	3.7854	3.7638	3.7683

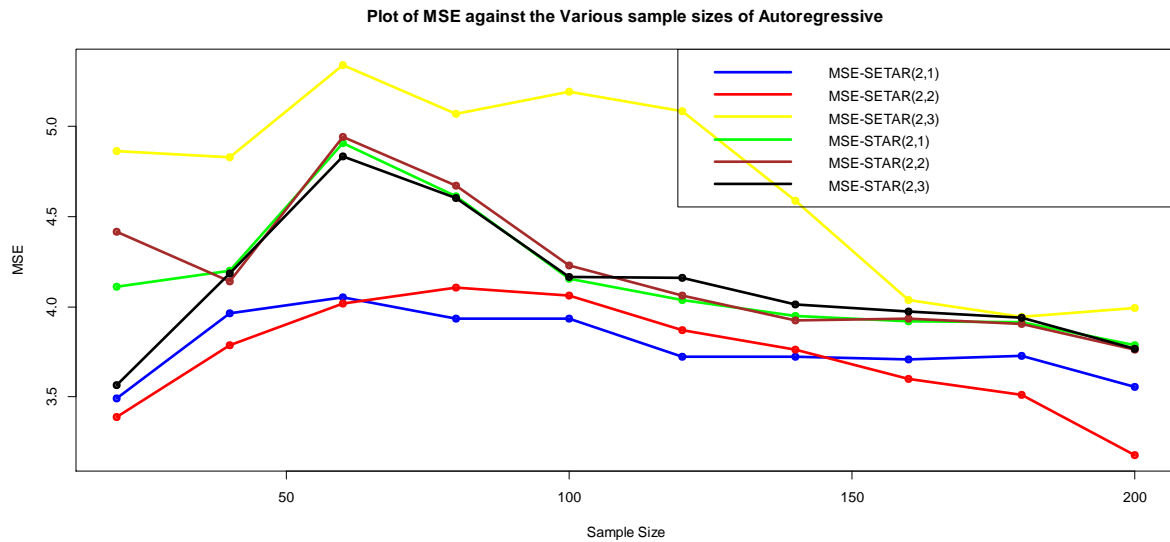


Figure 1: MSE of the fitted models on linear AR

Table 2: MAPE of SETAR and STAR Models across the Sample Sizes Fitted on AR: $X_{ti} = 0.7X_{ti-1} - 0.6X_{ti-2} + e_t$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	0.1191	0.1198	0.1196	0.1195	0.1197	0.1192
40	0.1187	0.1198	0.1196	0.1195	0.1198	0.1190
60	0.1188	0.1199	0.1193	0.1195	0.1199	0.1190
80	0.1186	0.1196	0.1190	0.1192	0.1199	0.1187
100	0.1187	0.1195	0.1193	0.1193	0.1197	0.1189
120	0.1179	0.1196	0.1194	0.1192	0.1195	0.1184
140	0.1184	0.1195	0.1192	0.1193	0.1196	0.1182
160	0.1180	0.1195	0.1189	0.1188	0.1194	0.1181
180	0.1178	0.1194	0.1186	0.1183	0.1193	0.1180
200	0.1179	0.1195	0.1187	0.1187	0.1193	0.1182

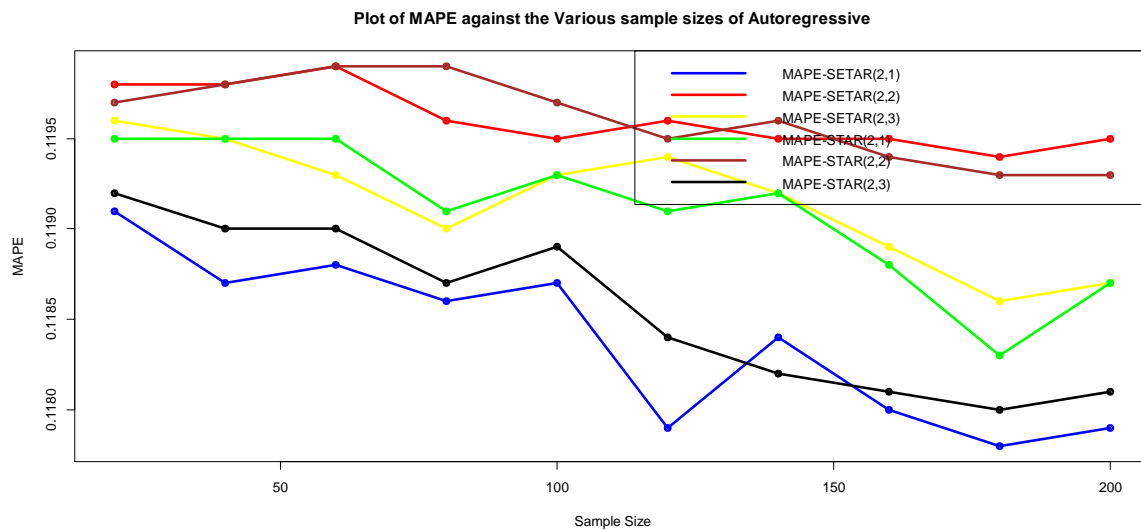


Figure 2: MASE of the fitted models on linear AR

Table 3: AIC of SETAR and STAR Models across the Sample Sizes Fitted on AR: $X_{ti} = 0.7X_{ti-1} - 0.6X_{ti-2} + e_t$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	39.0071	31.4197	38.8472	34.2640	35.7014	30.3998
40	63.1104	64.2440	99.3844	69.3870	67.8300	65.2588
60	101.9361	102.0535	145.4402	101.4427	101.8713	102.5476
80	129.4853	112.8418	213.8843	128.3188	129.2798	130.0890
100	150.9370	148.1906	247.2784	148.4934	150.1648	150.6457
120	171.8259	170.4354	254.7929	173.4744	174.2252	179.0462
140	197.9930	197.4720	255.5188	198.2904	197.4382	202.5348

160	223.6301	225.6387	268.5576	224.5566	225.1940	228.7234
180	250.8862	247.9722	275.4175	251.7081	251.2052	254.7187
200	267.8437	264.5026	288.6473	272.2327	271.0831	273.3267

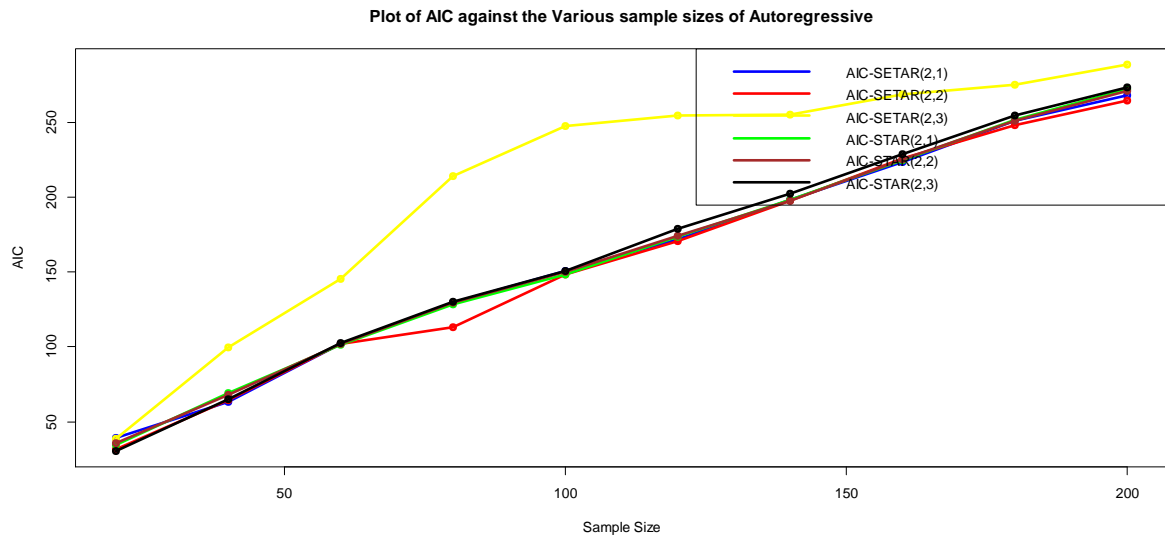


Figure 3: AIC of the fitted models on linear AR

Table 4: MSE of SETAR and STAR Models across the Sample Sizes Fitted on Trigonometric:

$$X_{ti} = 0.7 \sin(X_{t-1}) - 0.6 \cos X_{t-2} + e_t$$

Sample Size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	3.1317	3.9799	5.1181	4.9133	6.2620	2.9152
40	3.8272	4.0402	9.2536	4.6781	5.2848	4.3708
60	4.7649	5.2886	9.2200	5.0171	6.0036	5.0686
80	4.3264	5.0239	10.5929	5.0076	5.5915	5.1949
100	4.0247	4.4264	9.2359	4.0140	4.9518	4.4327
120	4.1275	4.3633	10.8565	4.1048	4.8799	4.5714
140	3.9586	4.1253	14.9776	3.9784	4.6057	4.2851
160	3.9487	4.0205	18.3391	3.8492	4.6082	4.3944
180	3.9404	3.9853	12.3866	3.6468	4.5457	3.9673
200	3.8162	3.9065	15.6097	3.5532	4.3554	4.4240

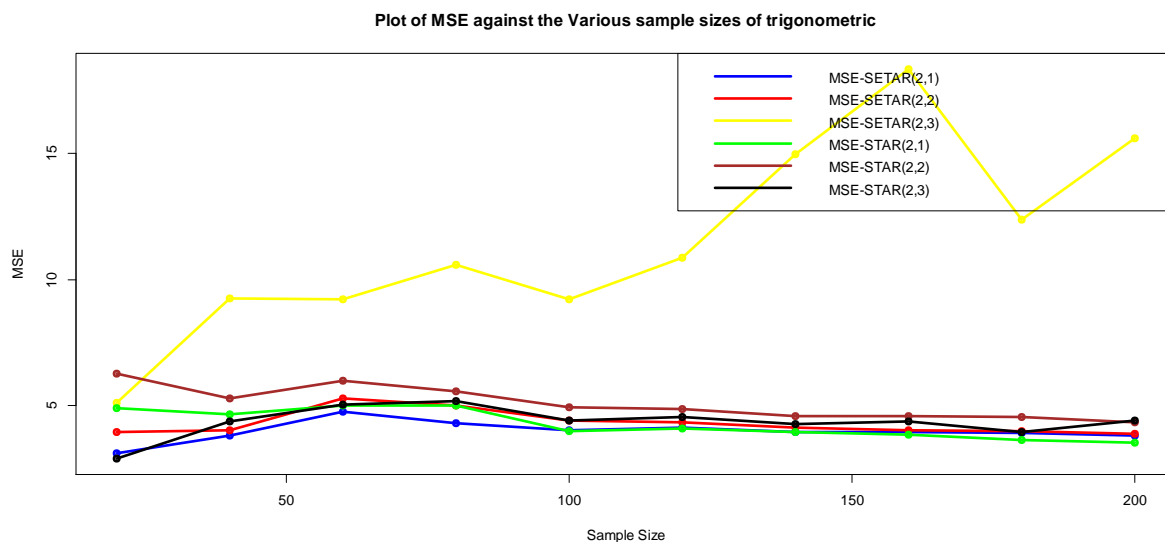


Figure 4: MSE of the fitted models on linear AR

Table 5: MAPE of SETAR and STAR Models across the Sample Sizes Fitted on Trigonometric:

$$X_{ti} = 0.7\sin(X_{ti-1}) - 0.6\cos X_{ti-2} + e_t$$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	1.8096	1.2232	0.3113	2.0948	1.7716	0.3272
40	1.6180	1.1999	0.6146	1.7030	1.3015	0.4018
60	2.1354	1.4137	0.7799	2.2351	1.5232	0.2263
80	1.7134	1.1274	0.2609	2.1014	1.5958	0.1241
100	1.5243	1.1416	0.2443	1.4898	1.2845	0.1790
120	1.7059	2.3918	0.9492	1.3879	2.2063	0.2119
140	1.6949	2.6559	0.4590	1.7847	2.8363	0.5093
160	1.6691	3.0106	0.3566	1.6834	3.9757	0.6079
180	1.6578	3.1846	0.4930	1.6911	3.2817	0.1740
200	1.5990	2.0819	0.9717	1.6339	3.5406	0.1868

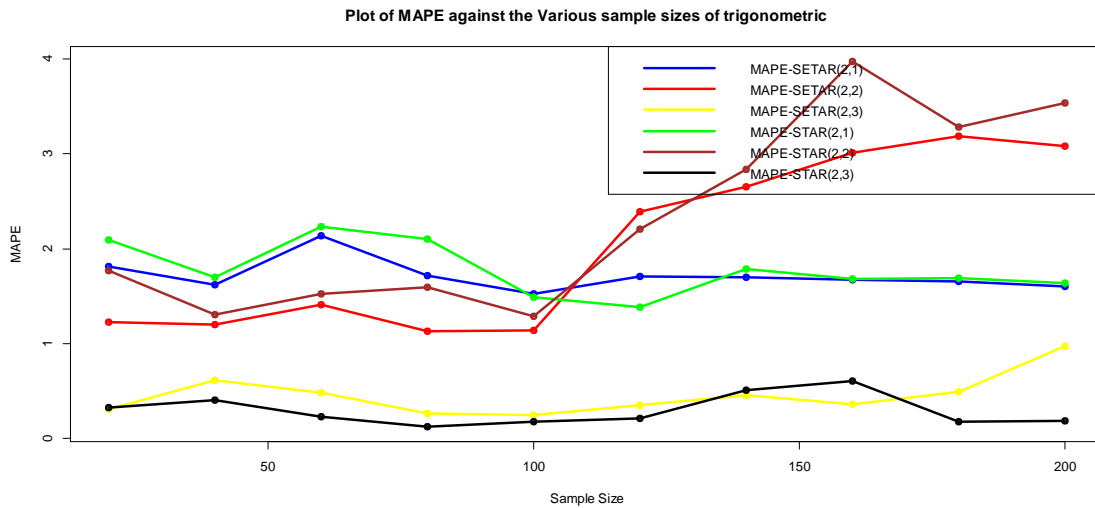


Figure 5: MAPE of the fitted models on linear AR

Table 6: AIC of SETAR and STAR Models across the Sample Sizes Fitted on Trigonometric:

$$X_{ti} = 0.7\sin(X_{ti-1}) - 0.6\cos X_{ti-2} + e_t$$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	36.8313	41.6249	29.0102	37.8389	42.6899	29.3989
40	67.6850	69.85207	132.3078	67.7157	72.5929	66.9982
60	107.6771	113.9337	216.4913	108.4712	113.5413	105.3834
80	131.1796	143.1360	247.8224	138.4694	143.7004	139.8138
100	153.2460	162.7592	333.0052	154.9776	165.9744	156.8997
120	184.1218	190.7881	363.8278	185.4591	196.2145	190.3778
140	206.6239	212.3983	399.2453	209.3212	219.8211	211.7200
160	233.7404	236.6254	402.7533	231.6594	250.4544	244.8519
180	260.8318	262.8701	479.2933	258.8910	278.5537	256.0564
200	281.8490	286.5255	523.4700	279.5675	300.2820	305.4102

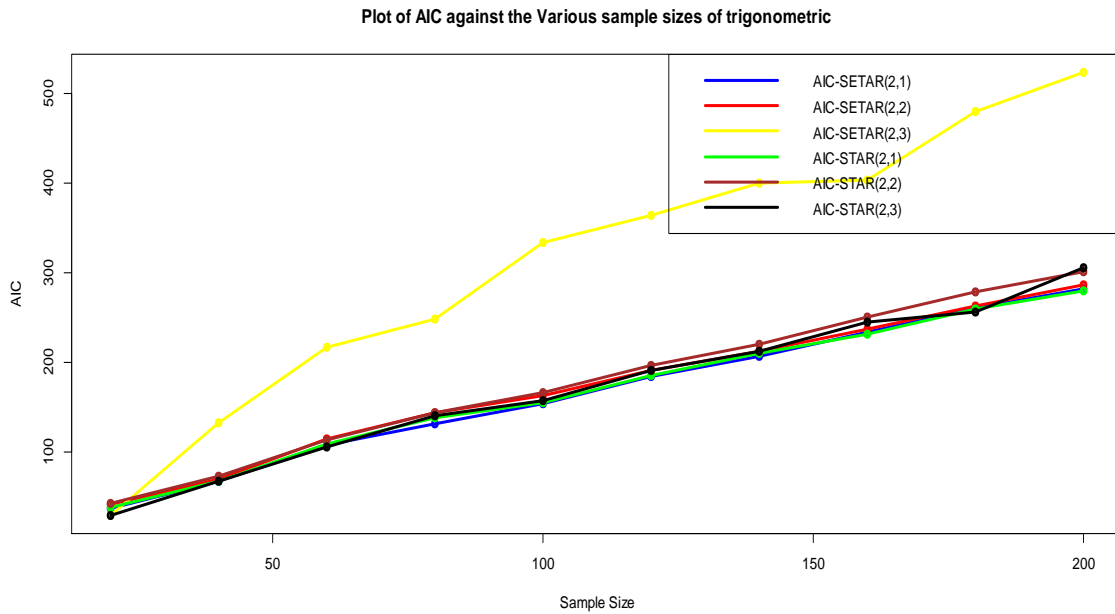


Figure 6: AIC of the fitted models on linear AR

Table 7: MSE of SETAR and STAR Models across the Sample Sizes Fitted on exponential:

$$X_{ti} = 0.7(X_{ti-1}) - \exp(0.6X_{ti-2}) + e_t$$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	3.02894	2.8190	3.6895	3.3292	4.2523	3.8184
40	3.6768	3.1874	5.9413	4.3560	4.1094	3.5792
60	4.3777	4.1330	6.5362	4.7981	4.8647	4.2307
80	4.3474	4.1861	6.5450	4.6497	4.6758	4.3435
100	4.1241	3.9152	6.2770	4.5205	4.2475	4.1224
120	4.0419	3.9094	5.4367	4.1803	4.1205	4.0421
140	3.9211	3.8008	5.7090	4.1060	4.0306	3.9237
160	3.9863	4.1000	4.6101	4.0739	4.3352	3.9861
180	4.0032	4.1030	4.7183	4.1407	4.1641	3.8738
200	3.8448	3.8091	4.8949	4.1562	3.9389	3.7661

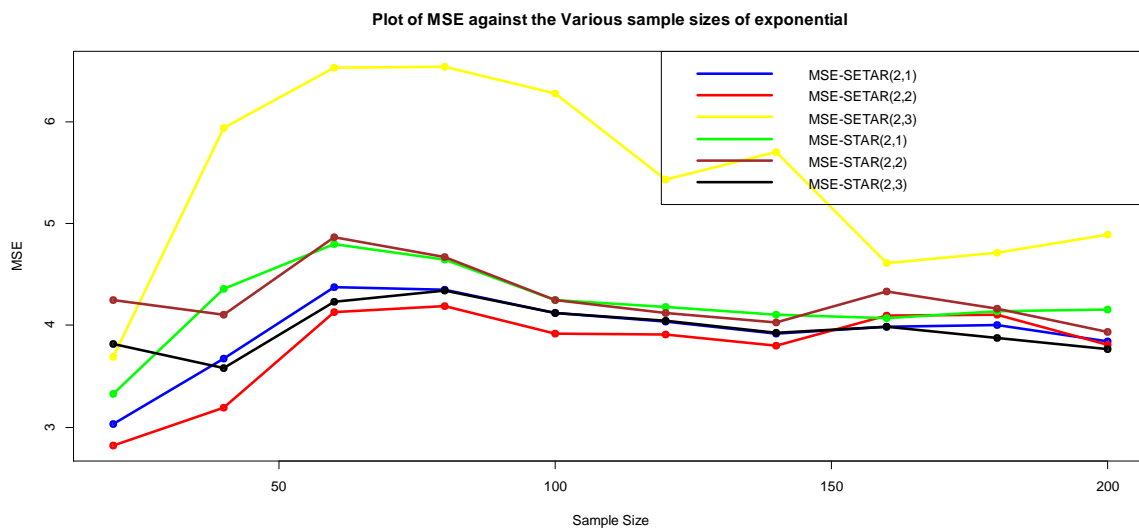


Figure 7: MSE of the fitted models on linear exponential

Table 8: MAPE of SETAR and STAR Models across the Sample Sizes Fitted on exponential:

$$X_{it} = 0.7(X_{it-1}) - \exp(0.6X_{it-2}) + e_t$$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	1.3342	0.4047	0.1393	2.2055	1.3890	0.0856
40	1.6161	0.9140	0.1453	1.5373	1.0737	0.0353
60	1.8865	1.1834	0.1516	2.0111	1.3406	0.0166
80	1.5033	1.1021	0.0433	1.4952	1.4610	0.0251
100	1.7352	1.0882	0.0691	1.7313	1.2953	0.0164
120	1.6202	1.1602	0.0795	1.6204	1.1695	0.0255
140	1.5126	1.0245	0.1535	1.5145	0.9938	0.0239
160	2.7140	0.9093	0.1059	2.7156	0.9457	0.0128
180	2.5708	1.2089	0.1491	2.7088	1.0777	0.0205
200	2.9151	1.1651	0.2868	3.0500	1.2230	0.0284

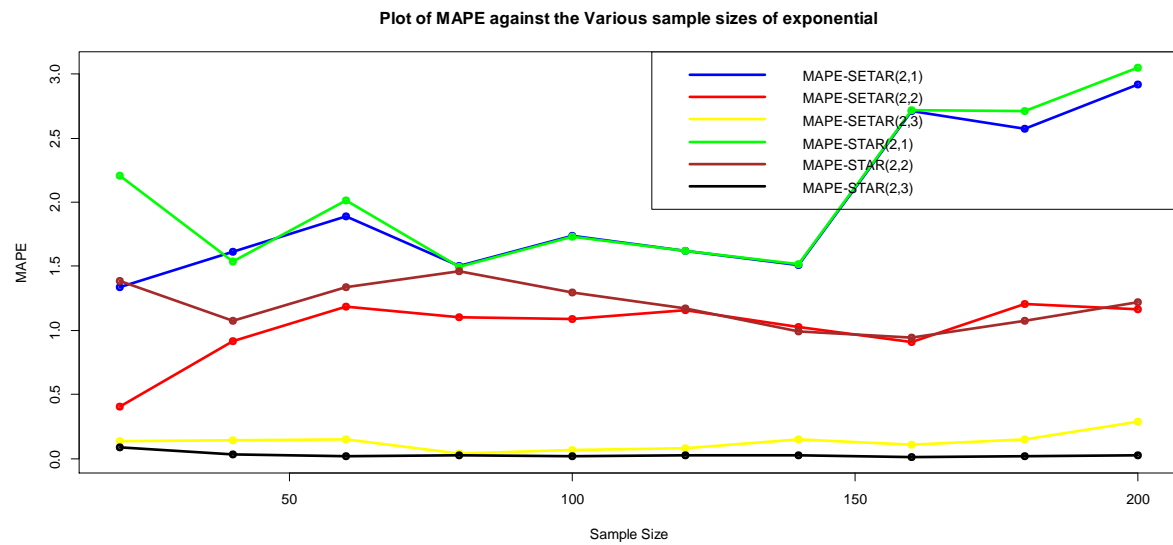


Figure 8: MAPE of the fitted models on linear exponential

Table 9: AIC of SETAR and STAR Models across the Sample Sizes Fitted on exponential:

$$X_{it} = 0.7(X_{it-1}) - \exp(0.6X_{it-2}) + e_t$$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	28.1502	34.7274	33.7870	37.4488	34.9490	32.0544
40	66.0818	60.3679	99.7018	66.8613	62.5307	66.8624
60	102.5909	99.1399	122.6586	108.6190	100.9202	102.0925
80	131.5660	128.5413	181.0831	133.4939	129.3918	130.9438
100	155.6841	150.4854	225.2943	157.6435	150.6339	152.6946
120	181.6056	177.6071	298.4070	183.6111	175.9158	179.6469
140	205.2917	200.9311	334.8540	207.3851	201.1480	192.3197
160	235.2588	231.6578	376.7380	237.2519	240.6836	228.7670
180	263.6756	258.8677	397.9810	259.7636	262.7697	254.1874
200	283.3450	271.4776	400.4040	281.2083	280.1821	266.0767

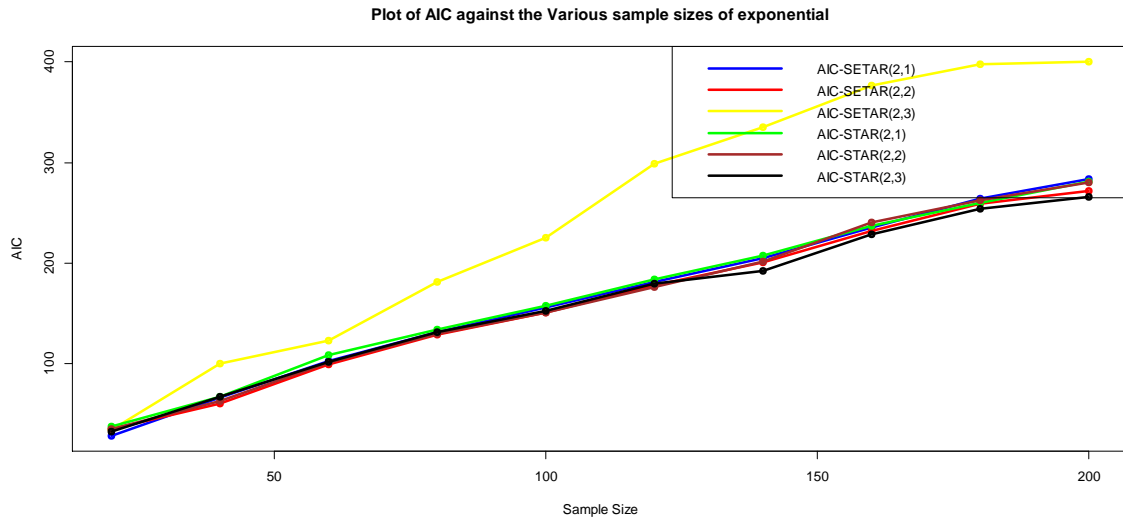


Figure 9: AIC of the fitted models on linear exponential

Table 10: MSE of SETAR and STAR Models across the Sample Sizes Fitted on polynomial:

$$X_{it} = 0.7(X_{it-1}^2) - 0.6(X_{it-2}) + e_t$$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	853.4312	587.3325	757.1245	645.3714	395.0563	745.3714
40	793.5645	477.3434	703.3665	585.3477	337.4387	725.3426
60	777.1982	398.0101	694.7014	503.1258	320.3332	703.1235
80	741.2009	387.4829	659.2508	567.5661	304.9870	687.5608
100	721.0786	218.8977	646.2354	517.8725	299.4432	657.7815
120	693.3134	197.4535	612.0578	414.1761	282.8970	624.1766
140	656.0975	193.7908	585.3008	460.1515	270.0070	616.1530
160	614.7413	190.0952	548.6817	415.3444	190.0170	595.3423
180	583.3406	190.0163	517.3045	387.2332	189.3435	587.2315
200	551.9715	189.8818	492.1313	377.1748	179.6745	567.1702

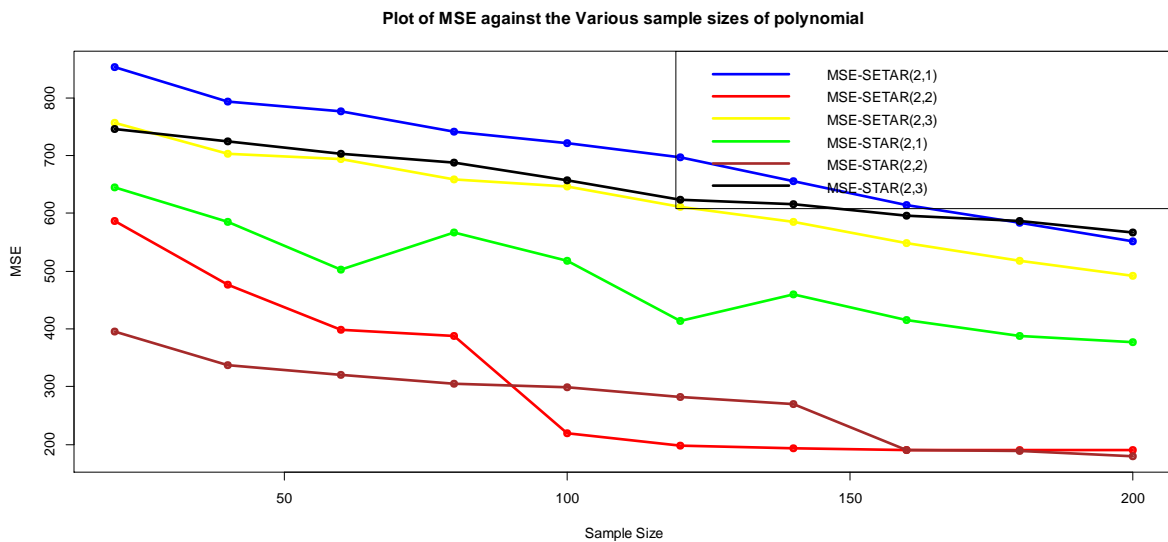


Figure 10: MSE of the fitted models on linear polynomial

Table 11: MAPE of SETAR and STAR Models across the Sample Sizes Fitted on polynomial:

$$X_{ti} = 0.7(X_{ti-1}^2) - 0.6(X_{ti-2}) + e_t$$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	1340.7926	980.6726	1995.2816	1897.5615	18.0715	1255.9872
40	1320.4634	943.7916	1875.5932	1858.2432	17.6511	1243.0681
60	1318.8533	898.0138	1846.5414	1787.5018	17.2596	1223.0994
80	1298.3176	552.9945	1787.3855	1508.1065	16.7551	1204.0231
100	1257.6158	521.8885	1654.4346	1210.8366	16.5065	1169.0772
120	1244.9438	396.4515	1574.4774	1198.8048	16.1365	1172.0032
140	1216.2613	389.9954	1327.0113	1186.8262	16.0938	1156.7621
160	1183.6763	382.0065	1225.5437	1156.9183	15.9967	1135.0931
180	1165.5827	367.8916	1203.2573	1123.6213	15.6539	1124.8775
200	1153.0547	367.8731	1162.7307	1020.4163	15.3027	1090.0752

Plot of MAPE against the Various sample sizes of polynomial

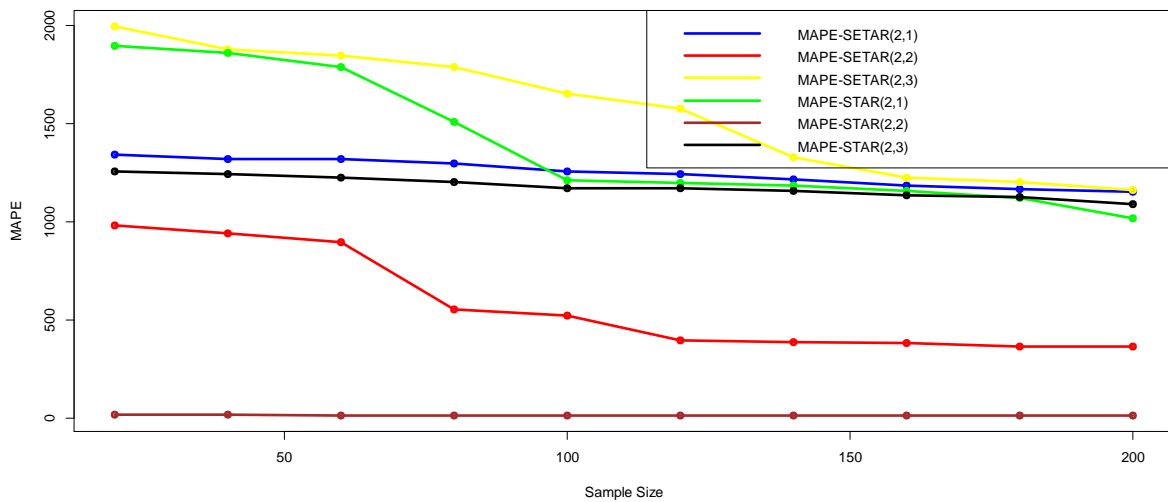


Figure 11: MAPE of the fitted models on linear polynomial

Table 12: AIC of SETAR and STAR Models across the Sample Sizes Fitted on polynomial:

$$X_{ti} = 0.7(X_{ti-1}^2) - 0.6(X_{ti-2}) + e_t$$

Sample size	setar(2,1)	setar(2,2)	setar(2,3)	star(2,1)	star(2,2)	star(2,3)
20	1340.7912	980.6720	1995.2842	1997.5645	118.0715	1010.0173
40	1150.4624	943.7914	1875.5967	1858.2445	117.6511	1009.1632
60	1188.8505	898.0165	1786.5432	1787.5050	117.2596	918.7866
80	1108.3111	552.9954	1687.3822	1508.1068	116.7551	918.7016
100	1097.6128	521.8885	1664.4313	1210.8318	116.5065	908.6115
120	1074.9462	396.4519	1574.4708	998.8074	116.1365	908.5015
140	1046.2612	389.9903	1527.0154	886.8266	116.0938	908.4335
160	1033.6735	382.0054	1485.5414	860.9141	115.9967	908.2214
180	1027.5814	367.8913	1453.2584	753.6258	115.6539	872.1825
200	1013.0575	367.8754	1362.7303	720.4166	115.3027	821.1074

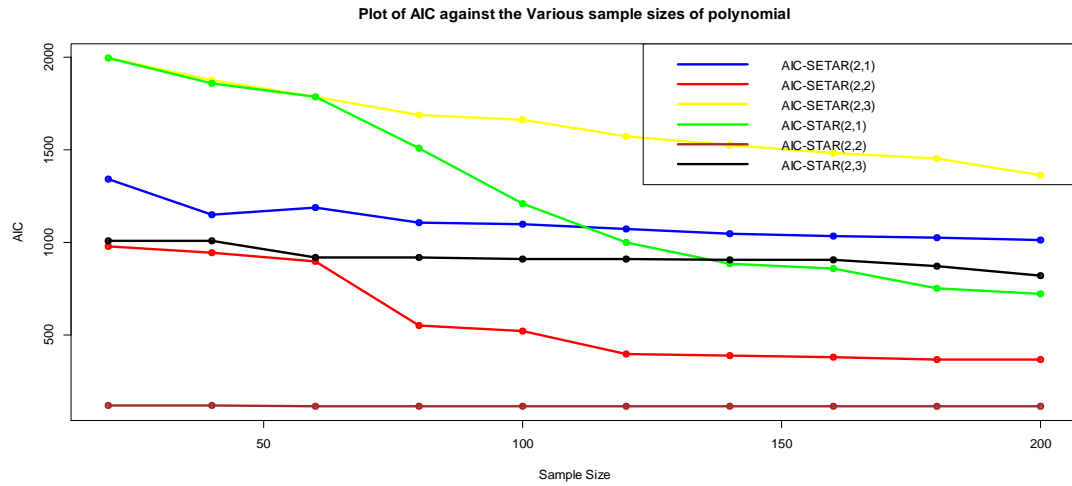


Figure 12: AIC of the fitted models on linear polynomial

Table 13: MSE of the Forecast of the Best Models from AR: $X_{it} = 0.7X_{it-1} - 0.6X_{it-2} + e_t$

Sample Size	n=20		n=100		n=200	
Steps ahead (h)	setar (2,1)	setar (2,2)	setar (2,1)	setar (2,2)	setar (2,1)	setar (2,2)
5	1.18e-33	1.28e-33	1.11e-32	6.23e-34	1.20e-33	1.03e-32
10	1.16e-33	1.34e-32	1.28e-32	6.16e-34	1.28e-33	1.52e-32
15	1.99e-32	1.09e-32	9.42e-33	2.79e-33	4.57e-32	8.12e-33
20	2.67e-32	1.20e-32	7.61e-32	1.47e-32	4.61e-32	8.50e-33
25	2.07e-32	1.82e-32	3.65e-32	4.16e-33	5.21e-32	2.80e-32
30	2.48e-32	1.91e-32	2.48e-32	1.88e-32	5.58e-32	1.55e-32
35	1.09e-31	2.01e-33	4.52e-32	2.10e-34	7.76e-32	1.75e-32
40	4.11e-32	3.77e-34	5.69e-32	1.23e-32	7.56e-32	2.47e-32
45	5.24e-32	7.94e-33	8.19e-32	1.21e-32	8.27e-32	2.69e-32
50	4.73e-31	3.85e-31	8.65e-32	8.69e-32	9.24e-32	1.55e-32

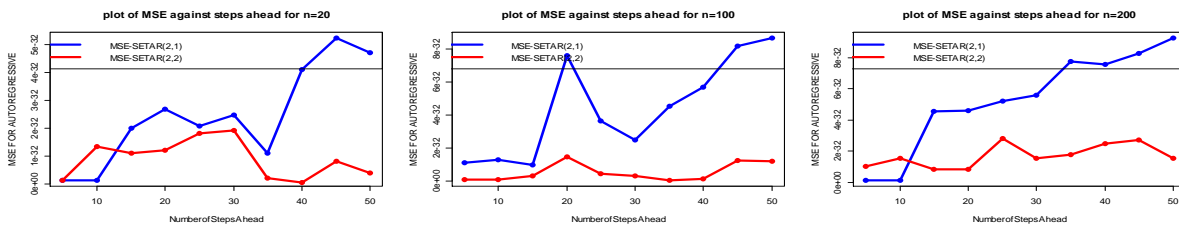


Table 14: AIC of the Forecast of the Best Models from AR: $X_{it} = 0.7X_{it-1} - 0.6X_{it-2} + e_t$

Sample Size	n=20		n=100		n=200	
Steps ahead (h)	setar (2,1)	Setar (2,2)	setar (2,1)	Setar (2,2)	setar (2,1)	Setar (2,2)
5	-1334.92	-1248.27	-1845.86	-2533.65	-1765.36	-2623.65
10	-963.56	-691.83	-1012.66	-1784.85	-1008.51	-2209.88
15	-1058.40	-1165.88	-1054.62	-2053.01	-1063.69	-2375.66
20	-1416.88	-1483.91	-1126.80	-2242.51	-1415.46	-2486.88
25	-1820.95	-1885.34	-1276.71	-2358.38	-1509.41	-2499.80
30	-1973.35	-2594.84	-1553.26	-2559.43	-1692.35	-2560.91
35	-1982.94	-2615.02	-1694.32	-2658.07	-1720.35	-2586.49
40	-2077.78	-2751.49	-1858.98	-2744.65	-1812.59	2605.20
45	-2290.65	-2945.85	-2089.80	-2807.97	-1878.93	-2752.65
50	-2221.36	-2962.23	-2158.43	-2911.28	-1944.77	-2813.29

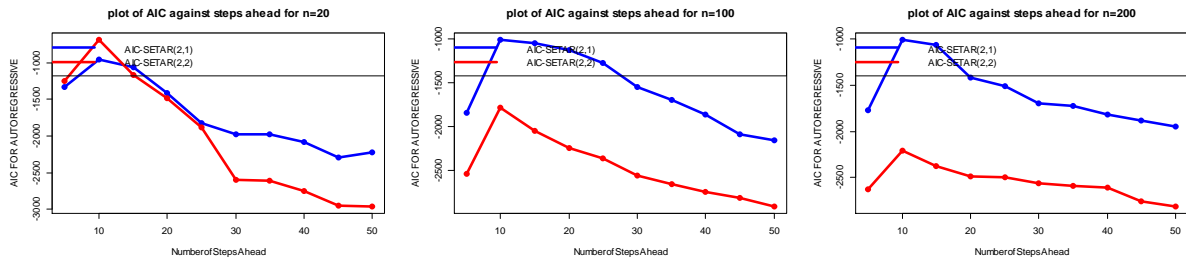


Table 15: MSE of the Forecast of the Best Models from Trigonometric AR (2):

$$X_{ti} = 0.7 \sin(X_{ti-1}) - 0.6 \cos(X_{ti-2}) + et$$

Sample Size	n=20		n=100		n=200	
Steps ahead (h)	setar (2,1)	star (2,1)	setar (2,1)	star (2,1)	setar (2,1)	star (2,1)
5	3.96e-32	1.19e-32	6.15e-33	2.37e-33	5.32e-33	2.34e-33
10	4.66e-32	3.24e-33	6.59e-33	2.85e-33	4.66e-33	2.09e-33
15	3.51e-32	7.79e-34	5.58e-33	2.04e-33	9.50e-33	2.95e-33
20	4.44e-32	5.64e-33	6.90e-33	2.27e-33	8.58e-33	2.30e-33
25	5.10e-32	5.68e-33	5.10e-33	2.08e-33	9.48e-33	2.49e-33
30	3.15e-32	5.03e-34	5.83e-33	2.35e-33	8.13e-33	2.21e-33
35	9.04e-32	1.05e-32	5.82e-33	2.35e-33	9.05e-33	2.03e-33
40	4.47e-32	1.45e-32	5.68e-33	2.73e-33	8.39e-33	2.42e-33
45	4.29e-32	7.37e-33	5.50e-33	2.10e-33	8.84e-33	2.27e-33
50	4.24e-32	1.84e-33	6.11e-33	2.34e-33	8.75e-33	2.03e-33

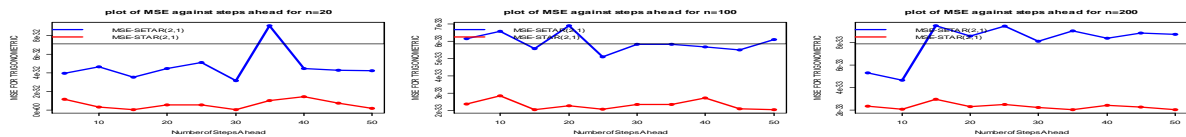


Table 16: AIC of the forecast of the best models from trigonometric: $X_{ti} = 0.7 \sin(X_{ti-1}) - 0.6 \cos(X_{ti-2}) + et$

Sample Size	n=20		n=100		n=200	
Steps ahead (h)	setar (2,1)	star (2,1)	setar (2,1)	star (2,1)	setar (2,1)	star (2,1)
5	-1328.93	-3328.54	-998.94	-1228.08	-1379.34	-2328.64
10	-750.29	-1749.28	-1019.96	-1752.73	-1036.60	-1750.27
15	-1117.91	-2002.77	-1013.73	-1825.30	-1147.93	-1905.52
20	-1376.63	-2187.14	-1083.49	-1924.29	-1269.26	-2583.81
25	-1444.05	-2035.41	-1027.15	-1999.58	-1273.40	-2895.70
30	-1553.53	-2267.84	-1085.12	-2239.38	-1304.14	-2828.10
35	-2002.23	-2590.20	-1193.86	-2233.04	-1577.55	-2905.76
40	-2287.60	-2990.80	-1411.71	-2263.58	-1975.73	-3137.97
45	-2344.87	-3081.43	-1458.42	-2358.52	-2126.52	-3064.65
50	-2356.05	-3023.79	-1512.53	-2408.25	-2091.44	-3198.36

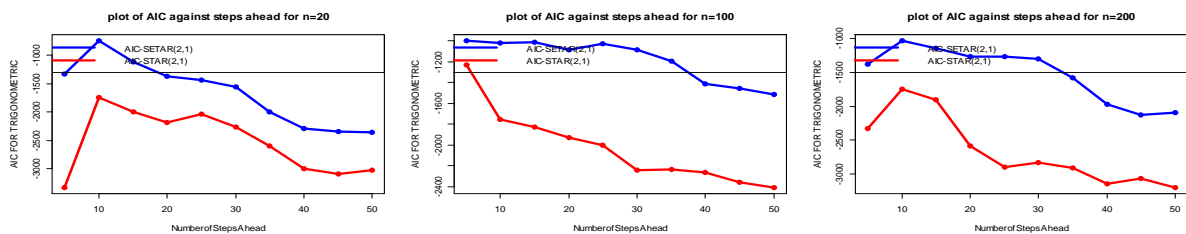


Table 17: MSE of the forecast of the best models from exponential: $X_{ti} = 0.7X_{ti-2} - exp(0.6X_{ti-2}) + et$

Sample Size	n=20		n=100		n=200	
Steps ahead (h)	setar (2,2)	Star(2,3)	setar (2,2)	Star(2,3)	setar (2,2)	Star(2,3)
5	1.67e-32	3.11e-31	4.15e-34	1.08e-33	2.98e-34	2.08e-32
10	1.31e-32	3.71e-31	5.82e-34	1.28e-32	3.63e-34	2.58e-32
15	1.10e-32	1.68e-31	4.54e-33	1.47e-32	5.92e-33	7.70e-32
20	1.07e-32	2.79e-31	3.59e-33	1.79e-32	7.08e-33	9.15e-32
25	1.14e-32	2.92e-31	5.15e-33	5.76e-32	6.37e-33	9.18e-32
30	1.14e-32	2.40e-31	5.83e-33	5.60e-32	4.37e-33	8.04e-32
35	1.26e-32	2.60e-31	8.32e-33	8.84e-32	4.48e-33	3.11e-31
40	1.37e-32	3.04e-31	1.11e-32	1.54e-31	3.29e-33	6.43e-32
45	1.48e-32	3.34e-31	1.94e-32	1.45e-31	4.54e-33	4.20e-32
50	1.62e-32	4.42e-31	1.13e-32	1.37e-31	4.37e-33	4.65e-31

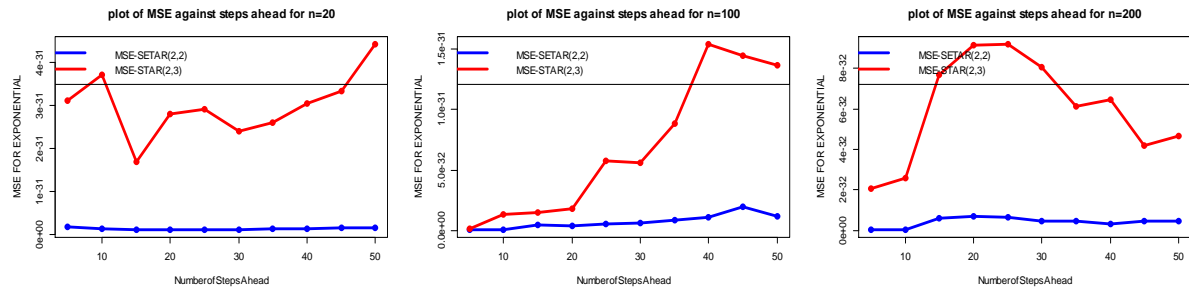


Table 18: AIC of the forecast of the best models from exponential: $X_{ti} = 0.7X_{ti-1} - exp(0.6X_{ti-2}) + et$

Sample Size	n=20		n=100		n=200	
Steps ahead (h)	setar (2,2)	star (2,3)	setar (2,2)	star (2,3)	setar (2,2)	star (2,3)
5	-1523.79	-978.44	-1713.79	-981.443	-1981.43	-1000.79
10	-1995.29	-995.29	-1812.34	-1009.2899	-2105.0211	-1119.78
15	-2129.71	-1034.82	-1829.71	-1110.82	-2451.975	-1189.71
20	-2364.74	-1375.50	-1911.83	-1217.504	-2441.269	-1211.834
25	-2424.09	-1445.65	-2153.74	-1280.654	-2680.202	-1253.744
30	-2493.67	-1511.80	-2366.46	-1235.80	-2716.947	-1356.56
35	-2768.97	-1668.80	-2579.92	-1295.82	-2763.372	-1389.78
40	-2893.46	-1773.30	-2663.03	-1315.34	-2844.455	-1497.58
45	-3108.93	-1980.92	-2778.56	-1468.93	-3220.099	-1587.33
50	-3136.40	-2106.79	-2800.67	-1459.63	-3220.974	-1645.43

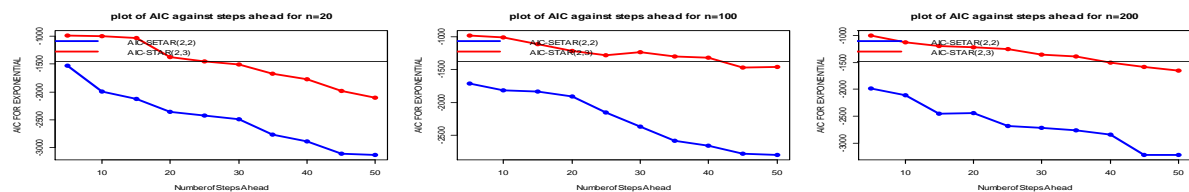


Table 19: MSE of the forecast of the best models from polynomial: $X_{ti} = 0.7X_{ti-1}^2 - 0.6X_{ti-2} + e_t$

Sample Size	n=20		n=100		n=200	
Steps ahead (h)	Setar(2,2)	Star(2,2)	Setar(2,2)	Star(2,2)	Setar(2,2)	Star(2,2)
5	2.91e-06	0.0040	2.33e-04	6.22e-04	2.91e-06	0.0040
10	9.10e-07	0.0038	9.57e-05	5.81e-04	9.10e-07	0.0038
15	6.05e-07	0.0038	7.45e-05	5.14e-04	6.05e-07	0.0038
20	4.87e-07	0.0038	5.00e-05	4.97e-04	4.87e-07	0.0038
25	3.54e-07	0.0035	9.57e-06	4.83e-04	3.54e-07	0.0035
30	9.43e-08	0.0035	9.03e-06	4.77e-04	9.43e-08	0.0035
35	8.13e-08	0.0035	8.00e-06	3.43e-04	8.13e-08	0.0035
40	7.06e-08	0.0031	7.30e-06	2.32e-04	7.06e-08	0.0031
45	4.53e-08	0.0022	4.55e-06	1.92e-04	4.53e-08	0.0022
50	1.01e-08	0.0013	2.10e-06	1.77e-04	1.01e-08	0.0013

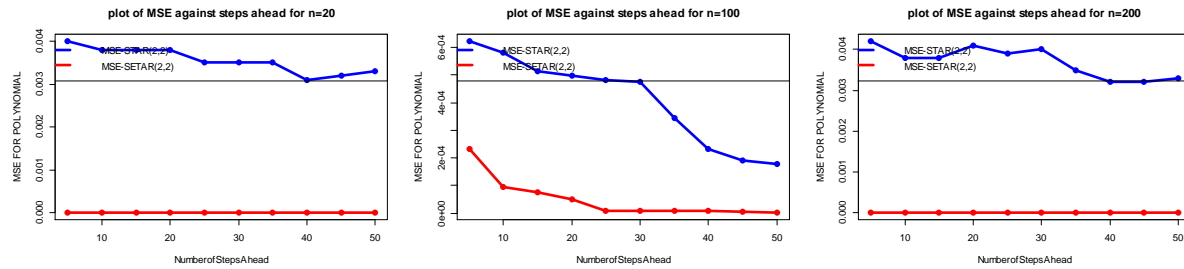
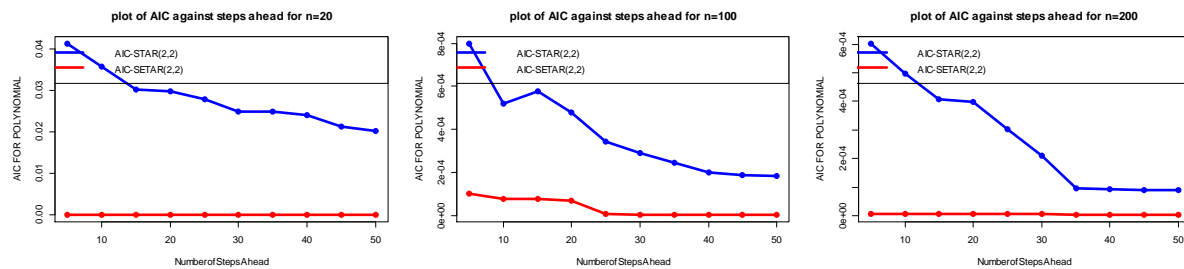


Table 20: AIC of the forecast of the best models from polynomial: $-X_{it} = 0.7X_{it-1}^2 - 0.6X_{it-2} + e_t$

Sample Size	n=20		n=100		n=200		
	Steps ahead (h)	Setar(2,2)	Star(2,2)	Setar(2,2)	Star(2,2)	Setar(2,2)	Star(2,2)
5		9.15e-06	0.0412	9.89e-05	7.98e-04	5.22e-06	6.01e-04
10		7.33e-06	0.0358	7.75e-05	5.20e-04	6.02e-06	4.98e-04
15		6.45e-06	0.0302	7.56e-05	5.77e-04	5.51e-06	4.07e-04
20		4.44e-06	0.0297	6.88e-05	4.78e-04	5.88e-06	3.98e-04
25		3.16e-06	0.0279	5.07e-06	3.42e-04	5.07e-06	3.02e-04
30		1.14e-06	0.0248	4.06e-06	2.89e-04	5.06e-06	2.09e-04
35		7.11e-07	0.0249	3.77e-06	2.43e-04	4.07e-06	9.43e-05
40		5.58e-07	0.0181	3.11e-06	2.00e-04	3.87e-06	9.12e-05
45		5.01e-07	0.0172	1.78e-06	1.88e-04	2.92e-06	8.88e-05
50		4.89e-07	0.0143	1.59e-06	1.81e-04	2.88e-06	7.21e-05



Summary of Findings

This study focuses on investigating the relative performance of two nonlinear thresholds autoregressive with two regimes namely SETAR and STAR models. Their forecasting performance were studied on three common forms of nonlinear functions, these are polynomial, exponential and trigonometric. Simulated data with features of nonlinearity and non-stationarity was used to compare the performance of the model. The relative performance of each model was examined with a view to identifying the best models using the following criteria, mean square error (MSE), Akaike Information Criteria (AIC) and Mean Absolute Percentage Error (MAPE). The results for the 2- regime SETAR and STAR models of order 1, 2 and 3 were discussed as follows: For the linear auto regressive models, the SETAR (2, 1) performs better than the other models followed by SETAR (2, 2) on the basis of the MSE and AIC criteria. Whereas the MAPE criteria shows STAR (2, 3) is better than others in relative performance of the model. Hence, since two among the three criteria shows that the SETAR (2, 1) and SETAR (2, 2) were selected to be the best in forecasting the linear auto regressive models. Nevertheless, for the trigonometric nonlinear functions, it can be seen that SETAR (2, 1) and STAR (2, 1) are known to be the best based on the MSE and the AIC criteria and we therefore conclude that the two mentioned models were used for the best forecasting performance of the fitted models across the steps ahead. Moreover, the SETAR (2, 2) performs better for the MSE and the AIC criteria and STAR (2, 3) was

considered to be the best based on all of the three criteria in an exponential nonlinear function. The SETAR (2, 2) and the STAR (2, 2) were known to be the best models for the relative performance of the models. Finally, in determining the forecasting ability of the fitted models, the SETAR (2, 1) and SETAR (2, 2) are taken as the best models and therefore used to forecast for future values at different steps ahead for an Auto regressive form of linear function. The SETAR (2, 1) and STAR (2, 1) for the trigonometric form, the SETAR (2, 2) and STAR (2, 3) for an exponential and the SETAR (2, 2) and STAR (2, 2) for a polynomial nonlinear function. The MSE and AIC of the values of the forecasted models are recorded to compare the relative forecast performance of the models at lower, moderate and large sample sizes respectively. It was recorded that, in linear form of autoregressive, SETAR (2, 2) forecasted better than SETAR (2, 1) from the low to the high steps ahead for all of the sample sizes. However, the SETAR (2, 1) superseded SETAR (2, 2) at the lowest steps when the sample is 20 and 200 in forecasting the 5 step ahead while SETAR (2, 2) took the lead as the step ahead increases based on the criteria. The STAR (2, 1) outperforms the SETAR (2, 1) in trigonometric function from small, moderate and large sample sizes. As the steps ahead increases, the self-exciting threshold auto regressive model tends to come closer to the smooth transition auto regressive model., the results of exponential and polynomial functions show that SETAR (2, 2) was known to be the best model that can be used for forecasting.

CONCLUSION

In this study, comparative performances of the nonlinear models with non-stationarity features were carried out. SETAR and STAR models at order 1, 2 and 3 and regime 2 respectively was applied to AR, trigonometric, exponential and polynomial functions. It was concluded that SETAR (2, 2) forecasted better at different steps ahead on both AR and polynomial functions which is in line with the findings of Akeyede et al (2016). Whereas in forecasting trigonometric nonlinear form of data, it can be seen that STAR (2, 1) outperforms the other models. However, SETAR (2, 2) has shown to have the best forecasting performance for an exponential function.

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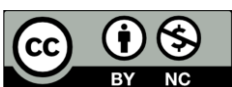
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