Forecasting Industrial Production of Electric and Gas Utilties in the United States of America

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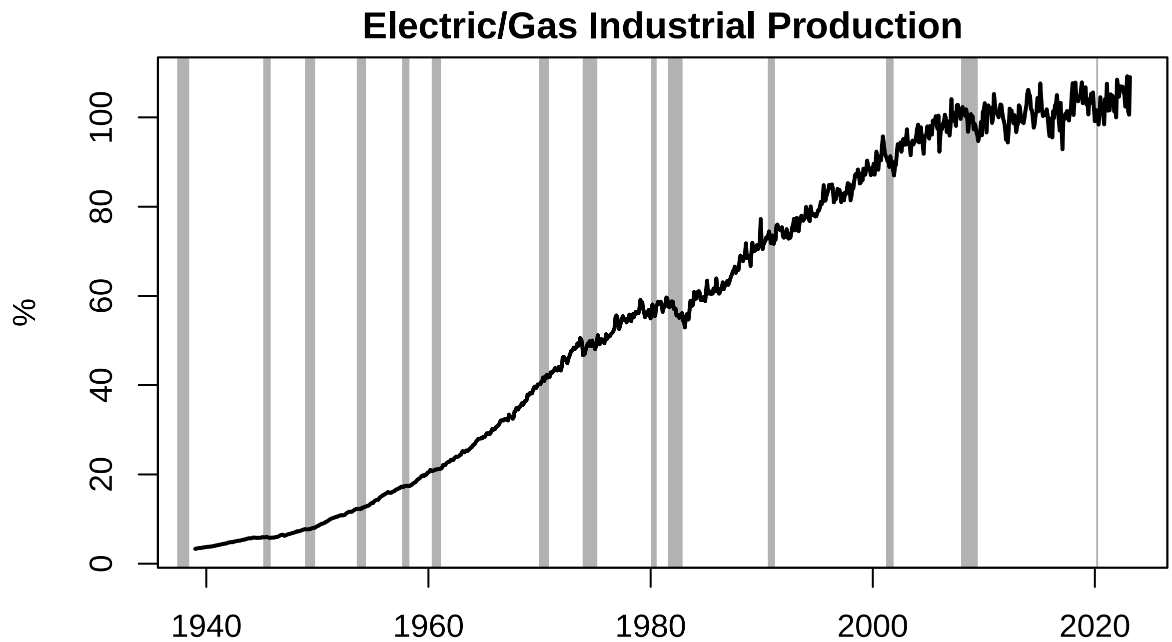
Introduction

The goal of this short report is to present the analysis undertaken to estimate a seasonal ARMA model in order to be able to forecast monthly Industrial Production of Electric and Gas Utilities in the United States of America. First, the data is briefly introduced. Next, the estimated model is presented and discussed. Finally, precision of the forecast using the seasonal ARMA model is compared to the precision of the naive forecasting method.

Data

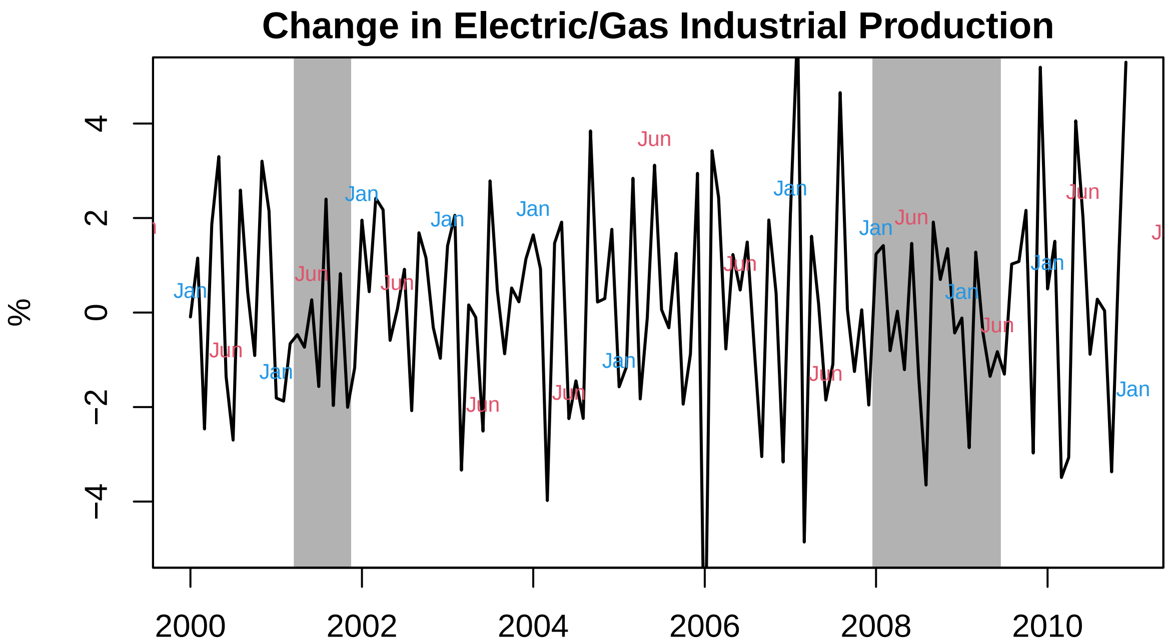
Monthly data for Industrial Production: Utilities: Electric and Gas Utilities for the period from July 1940 to December 2022 was obtained from FRED, where it is available under the code IPUTIL. Figure below shows the time series plot.



The estimation sample used to identify and estimate suitable model is January 1940 to December 2016. The remaining part, from January 2017 to April 2023 will be used to evaluate the precision of the forecast.To address stationary we have applied a first difference.

$y_t = \Delta IPUTIL_t = IPUTIL_t - IPUTIL_{t-1}$

Figure below shows this transformed time series y_t, which exhibits seasonal variation with significant spikes at multiples of 12. This is because the seasonality component of electric and gas facing higher demand during the winter months.



The correlogram of the change in the unemployment rate y_t shown in Appendix A confirms the presence of a seasonal pattern, reflected by a large spike in PAC at multiples of 12.

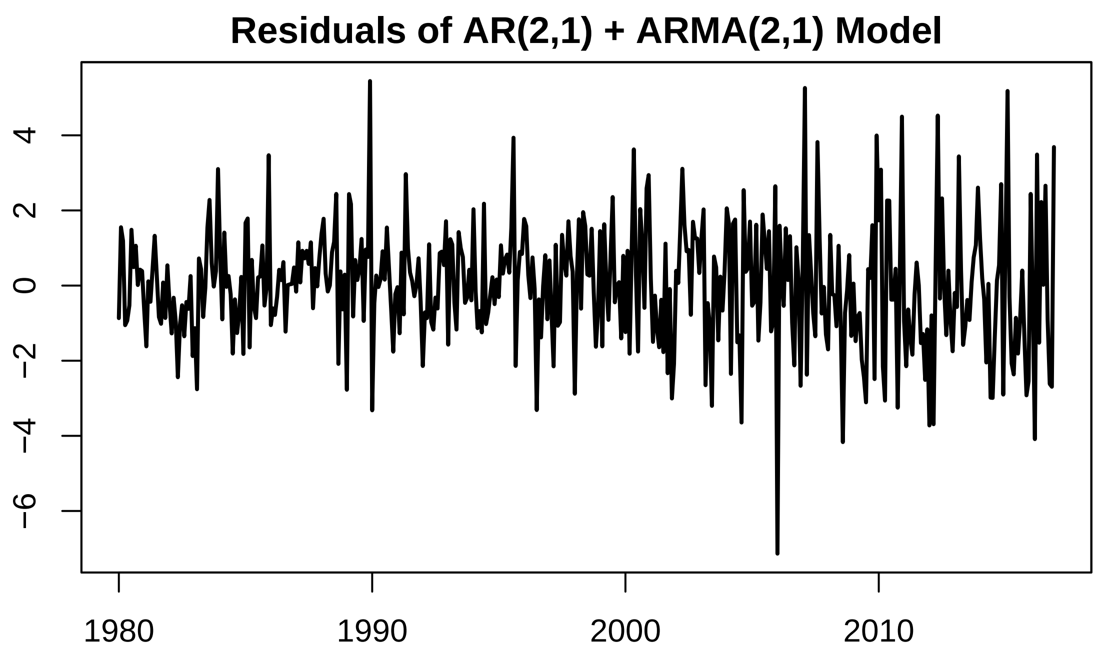
Model Estimation

To account for the seasonal pattern (large spikes at multiples of 12 in PAC) and the two large spikes at the beginning of the ACF. We have chosen

$$\Delta Y_t = \phi_1 \Delta Y_{t-1} + \phi_2 \Delta Y_{t-2} + \theta_1 e_{t-1} + \gamma_1 \Delta Y_{t-24} + \gamma_2 \Delta Y_{t-48} + \psi_1 e_{t-24}$$

Table below shows the results of the estimation

	Change in Electric/Gas Industrial Production
	AR(2,1) + S-ARMA(2,1)
ar1	0.434*** (0.010)
ar2	−0.077
ma1	−0.779*** (0.028)
sar1	−0.018
sar2	0.086
sma1	−0.265*** (0.034)
intercept	0.105*** (0.021)
Observations	444
Log Likelihood	−834.692
σ^2	2.500
Akaike Inf. Crit.	1,685.385
Note:	*p<0.1; **p<0.05; ***p<0.01



The estimated model takes this form:

$$\Delta Y_t = \phi_1 \Delta Y_{t-1} + \phi_2 \Delta Y_{t-2} + \theta_1 e_{t-1} + \gamma_1 \Delta Y_{t-24} + \gamma_2 \Delta Y_{t-48} + \psi_1 e_{t-24}$$

Forecast

As mentioned above, period from January 1980 to April 2023 was used as test sample to evaluate the precision of the forecast obtained using the estimated ARMA(2,1)-S-ARMA(2,1) model. First, a sequence of one step ahead forecasts was created, together with their 95% confidence interval. They are plotted in the figure below in red. The forecast follows the test data fairly closely demonstrating a decent ability to predict values.

Next, as a benchmark, a simple naive forecast was created for the change in unemployment rate in the same prediction sample January 1980 to April 2023 using

$f_{\mathbf{t,1}}^{\mathbf{naive}} = y_{t+1-12}$

This essentially means that the change in the industrial production(electric/gas) is predicted to be the same as it was in the same month one year ago. The implied forecast for Industrial production(electric/gas) $\mathbf{IPUTIL_{t,1}^{naive}}$ was afterwards calculated by adding the forecasted change in unemployment rate in the next month \$f_**t,1^naive** \$ to the actual unemployment rate in the current month $\mathbf{IPUTIL_{t,1}}$ that is, using $\mathbf{t,1^{IPUTILnaive}} = \mathbf{t,1^{IPUTILt+fnaive}}$ For both forecasts the forecast errors are calculated as $e_{\mathbf{t+1}} = y_{\mathbf{t+1}} - f_{\mathbf{t,1}}$ and are plotted in the figure above in red and green.

The forecast errors are quite large. The root mean squared error (RMSE) for forecast using the ARMA(2,1)-S-ARMA(2,1) model is 4.588, while the root mean squared error for forecast using naive forecasting method is 6.77. So, the ARMA(2,1)-S-ARMA(2,1) is generally better than the naive forecast.

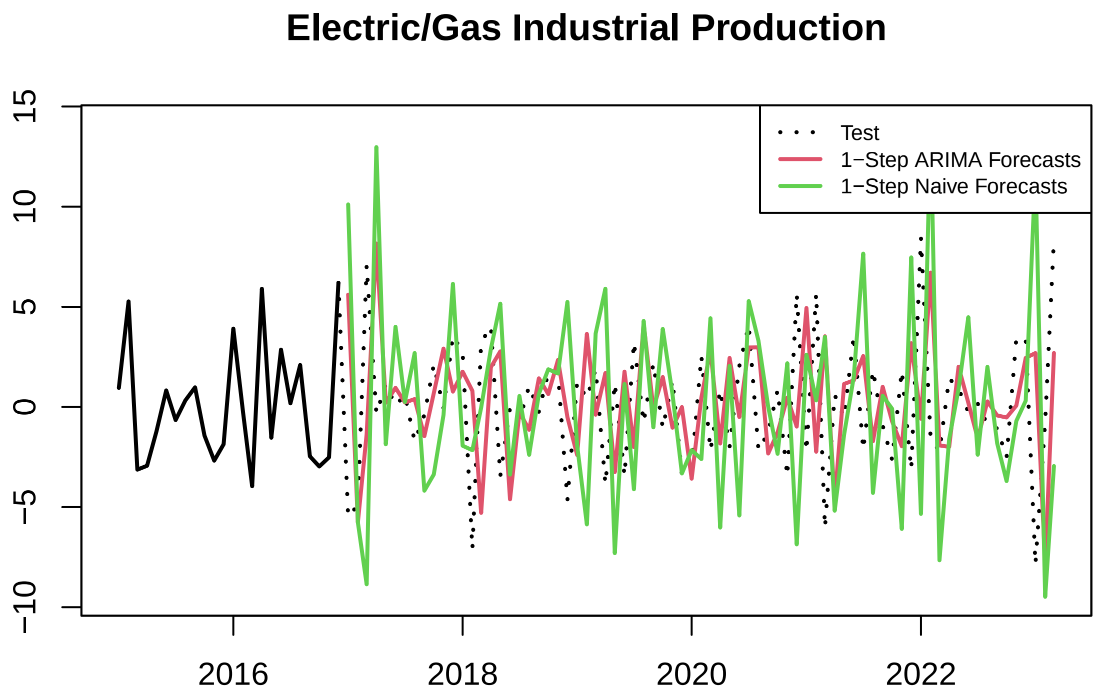
To determine whether the difference in the precision between the two forecasts is statistically significant or not, the test for the equal predictive ability was performed. This was done by estimating a simple regression model.

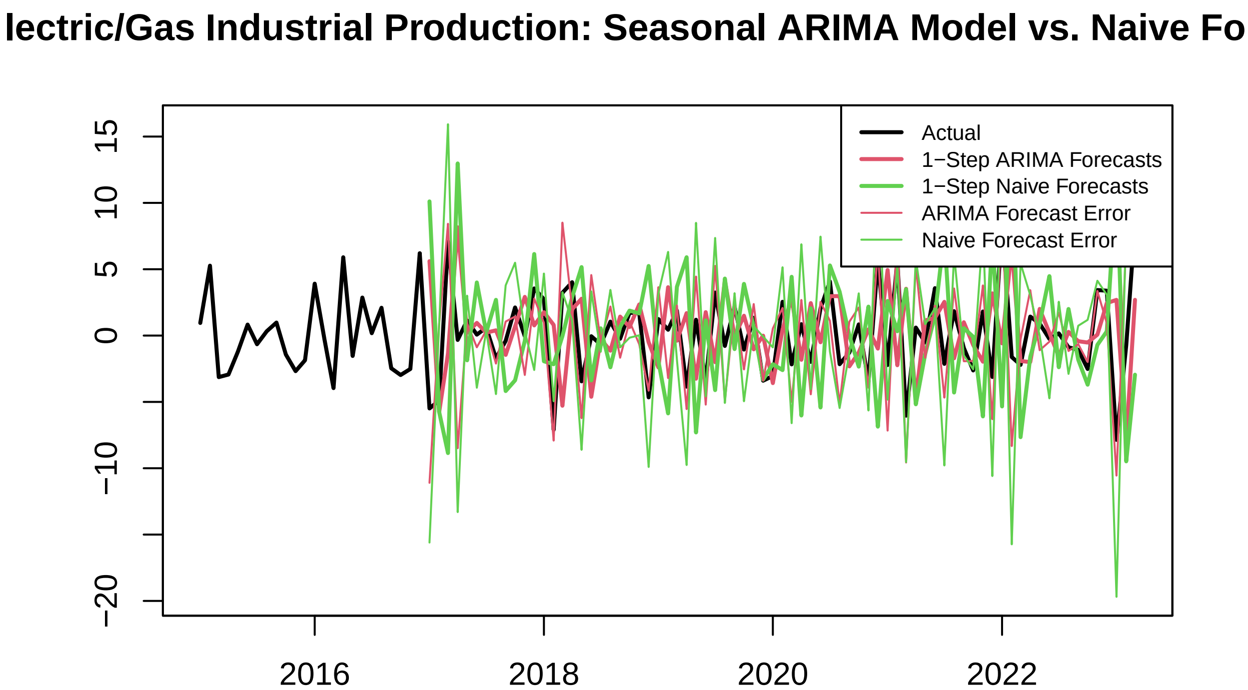
$$\Delta L_{t,1} = \beta_0 + u_t$$

where $\Delta L_{t,1}$ is the difference between the losses associated with the two alternative forecasts and testing the hypothesis $H_0 : \beta_0 = 0$. Rejecting this hypothesis means that the two model do not have equal predictive power. The results for the estimated regression show that the difference is statistically significant at 5% level, since p-value for

$$\beta_0$$

is 0.010. The ARMA(2,1)-S-ARMA(2,1) model did produce a significantly better forecast than a naive model.


Electric/Gas Industrial Production
Test
1−Step ARIMA Forecasts
1−Step Naive Forecasts
15
10
5
0
−5
−10
2016
2018
2020
2022

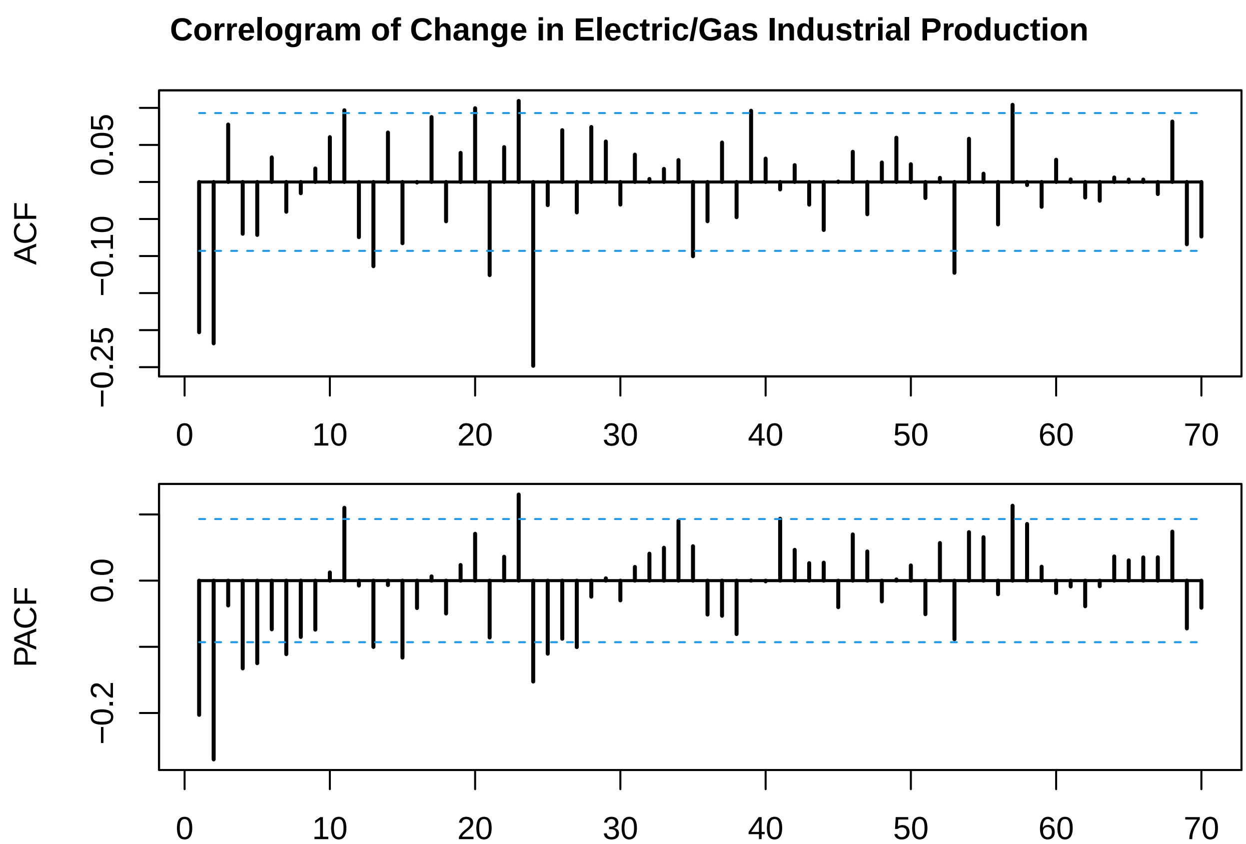


	Loss of ARIMA minus Naive Forecast
Constant	−24.776*** (6.032)
Period	Jan 2017 - Mar 2023
Observations	75
R^2	0.000
Adjusted R^2	0.000
Residual Std. Error	52.240 (df = 74)
Note:	*p<0.1; **p<0.05; ***p<0.01

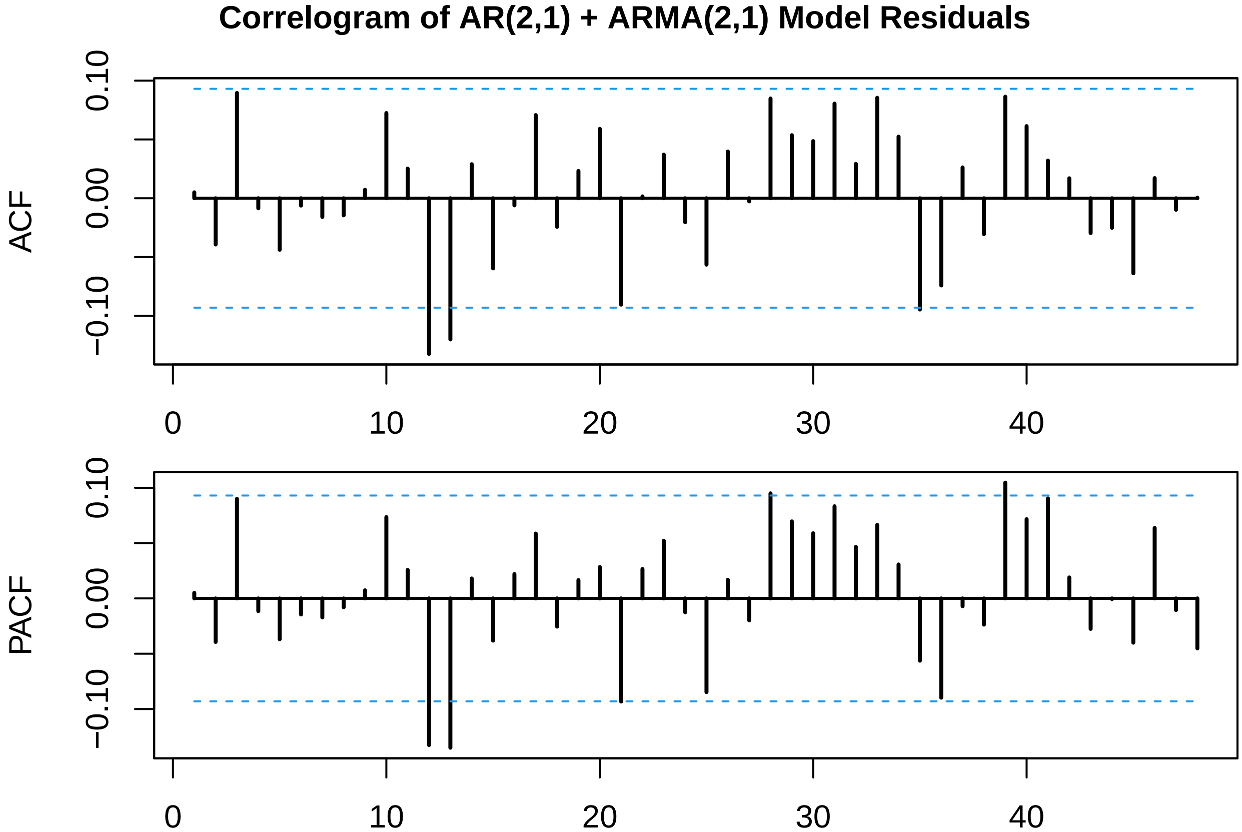
Conclusion

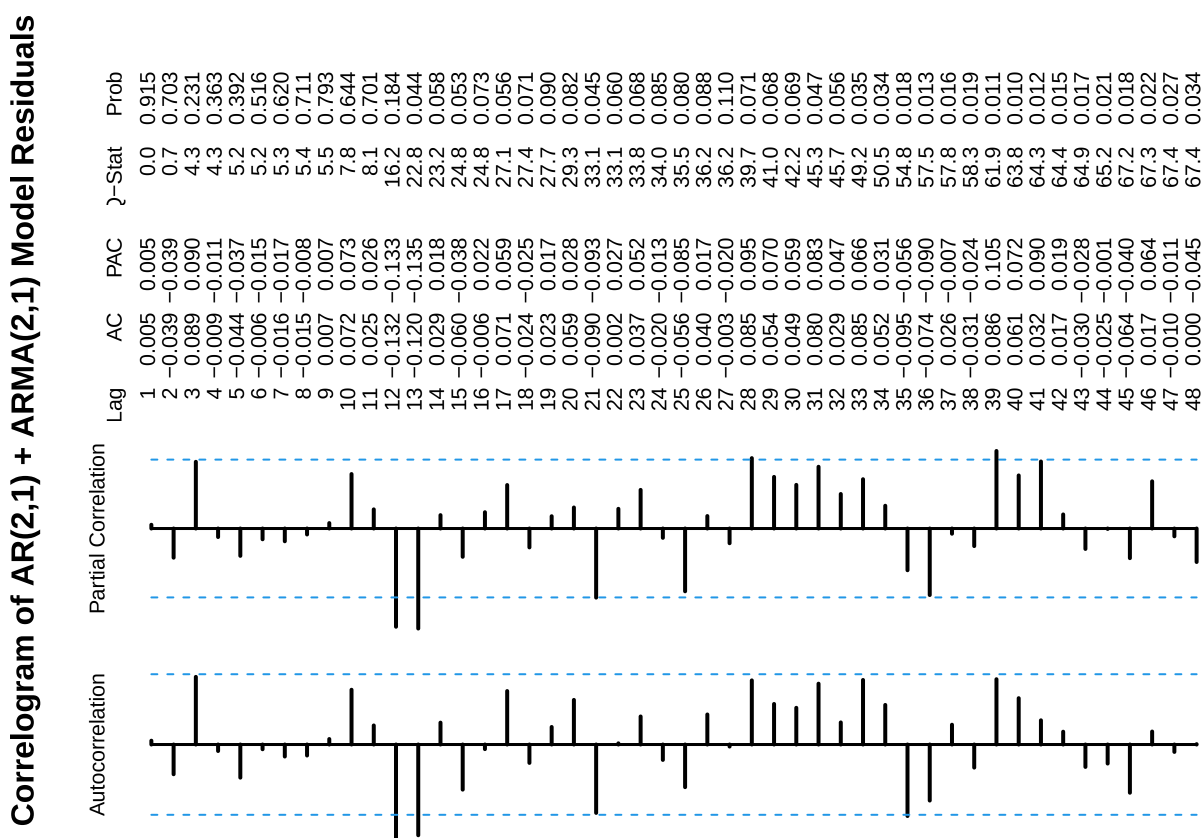
Forecasting Industrial Production of Electric and Gas Utilities can be forecast fairly well using a sample that goes far back. It performs much better than a naive model when we apply a first difference and consider seasonality. The estimated model is sufficient.

Apendix A


Correlogram of Change in Electric/Gas Industrial Production
ACF
0.05
−0.10
−0.25
0
10
20
30
40
50
60
70
PACF
0.0
−0.2
0
10
20
30
40
50
60
70

Apendix B





Lag	AC	PAC	Q-Stat	Prob
1	0.005	0.005	0.0	0.915
2	−0.039	−0.039	0.7	0.703
3	0.089	0.090	4.3	0.231
4	−0.009	−0.011	4.3	0.363
5	−0.044	−0.037	5.2	0.392
6	−0.006	−0.015	5.2	0.516
7	−0.016	−0.017	5.3	0.620
8	−0.015	−0.008	5.4	0.711
9	0.007	0.007	5.5	0.793
10	0.072	0.073	7.8	0.644
11	0.025	0.026	8.1	0.701
12	−0.132	−0.133	16.2	0.184
13	−0.120	−0.135	22.8	0.044
14	0.029	0.018	23.2	0.058
15	−0.060	−0.038	24.8	0.053
16	−0.006	0.022	24.8	0.073
17	0.071	0.059	27.1	0.056
18	−0.024	−0.025	27.4	0.071
19	0.023	0.017	27.7	0.090
20	0.059	0.028	29.3	0.082
21	−0.090	−0.093	33.1	0.045
22	0.002	0.027	33.1	0.060
23	0.037	0.052	33.8	0.068
24	−0.020	−0.013	34.0	0.085
25	−0.056	−0.085	35.5	0.080
26	0.040	0.017	36.2	0.088
27	−0.003	−0.020	36.2	0.110
28	0.085	0.095	39.7	0.071
29	0.054	0.070	41.0	0.068
30	0.049	0.059	42.2	0.069
31	0.080	0.083	45.3	0.047
32	0.029	0.047	45.7	0.056
33	0.085	0.066	49.2	0.035
34	0.052	0.031	50.5	0.034
35	−0.095	−0.056	54.8	0.018
36	−0.074	−0.090	57.5	0.013
37	0.026	−0.007	57.8	0.016
38	−0.031	−0.024	58.3	0.019
39	0.086	0.105	61.9	0.011
40	0.061	0.072	63.8	0.010
41	0.032	0.090	64.3	0.012
42	0.017	0.019	64.4	0.015
43	−0.030	−0.028	64.9	0.017
44	−0.025	−0.001	65.2	0.021
45	−0.064	−0.040	67.2	0.018
46	0.017	0.064	67.3	0.022
47	−0.010	−0.011	67.4	0.027
48	0.000	−0.045	67.4	0.034