Monthly Production of Clay Bricks

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Contents

Required R Packages

```
library(dplyr)
library(data.table)
library(astsa)
library(forecast)
```

Introduction

Bricks are used for building and pavement all throughout the world. In the USA, bricks were once used as a pavement material, and now it is more widely used as a decorative surface rather than a roadway material.("'Brick Manufacturing from Past to Present"' 1990) A healthy living environment especially requires the use of the right building material. In general building materials are strongly influencing the indoor climate and quality of living.("'Clay Brick Association of South Africa'," n.d.)

The aims of this study are to identify and forecast a model best fitting brick production data in the United States. The method of maximum likelihood was used to estimate the parameters and to forecast the number of production in the future. The data is a twenty year period from 1960 to 1980 and was obtained from the Time Series Data library at datamarket.com website. This project is of utmost importance and relevance because bricks are used for building and pavement all throughout the world. Being made from clay and shale, brick is most abundant and natural material on earth. In the USA, bricks were once used as a pavement material, and now it is more widely used as a decorative surface rather than a roadway material. A healthy living environment especially requires the use of the right building material. In general building materials are strongly influencing the indoor climate and quality of living.

Problem

The complexity of planning and constructing using clay bricks has increased in recent years.

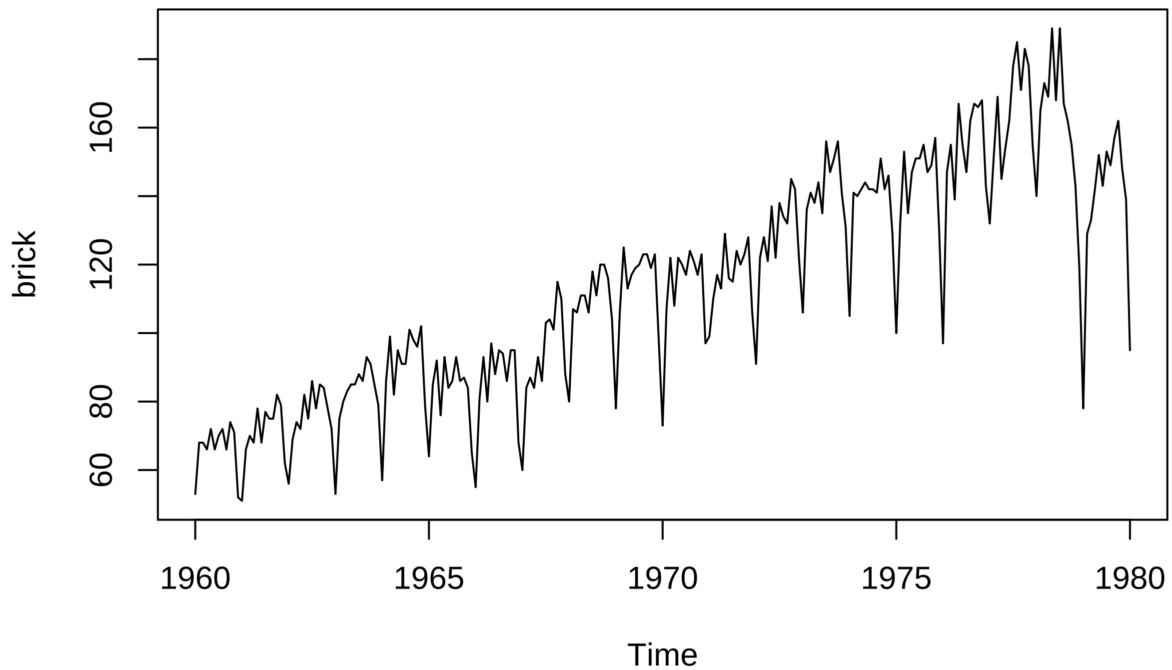
("'Wienerberger Clay Building Materials Europe'," n.d.)

Purpose

Result and Discussion

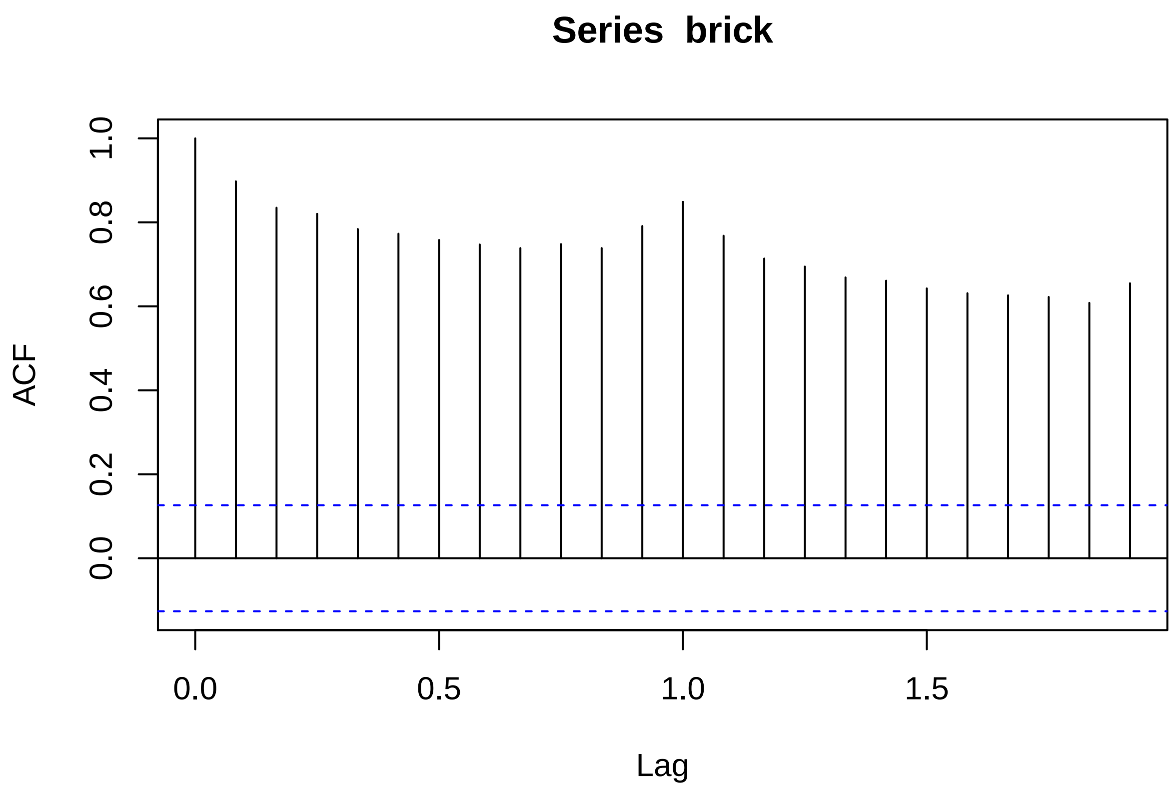
The data for the project was obtained from the Time Series Data library at datamarket.com. A snapshot of the table and line graph is shown in Figures 1 & 2. ("'Trends in Brick Plant Operations"' 1992)

```
data = ("https://raw.githubusercontent.com/wilsonify/TimeSeries/master/data/claybrick.csv")
columnNames = c("month", "production")
brick = read.csv(file = data,
                 comment.char = "",
                 header = TRUE,
                 col.names = columnNames)
brick = ts(brick$production, start = 1960, end = 1980, frequency = 12)
plot(brick)
```

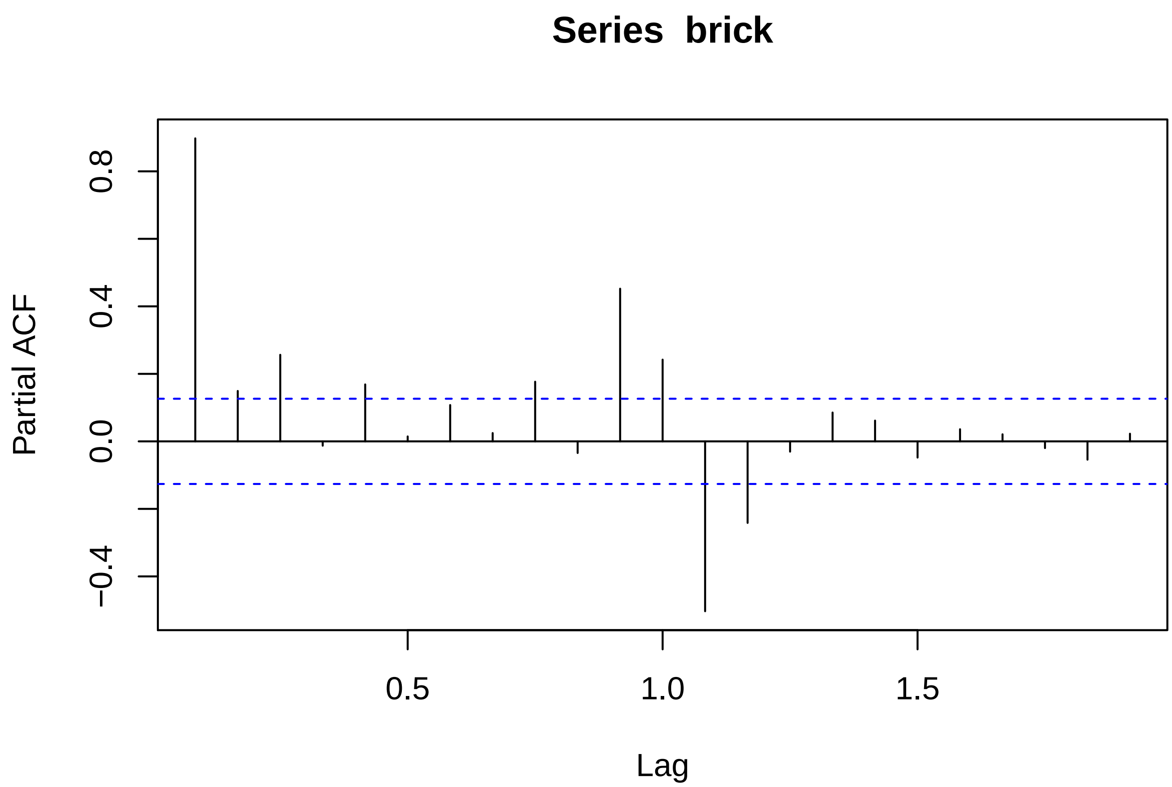


Since 1960, brick production has been trending up with clear seasonal fluctuations. A distinct trough is shown in 1979. The random fluctuations seem constant over time. Consider the autocorrelation at various lag time.

```r
acf(brick)
```

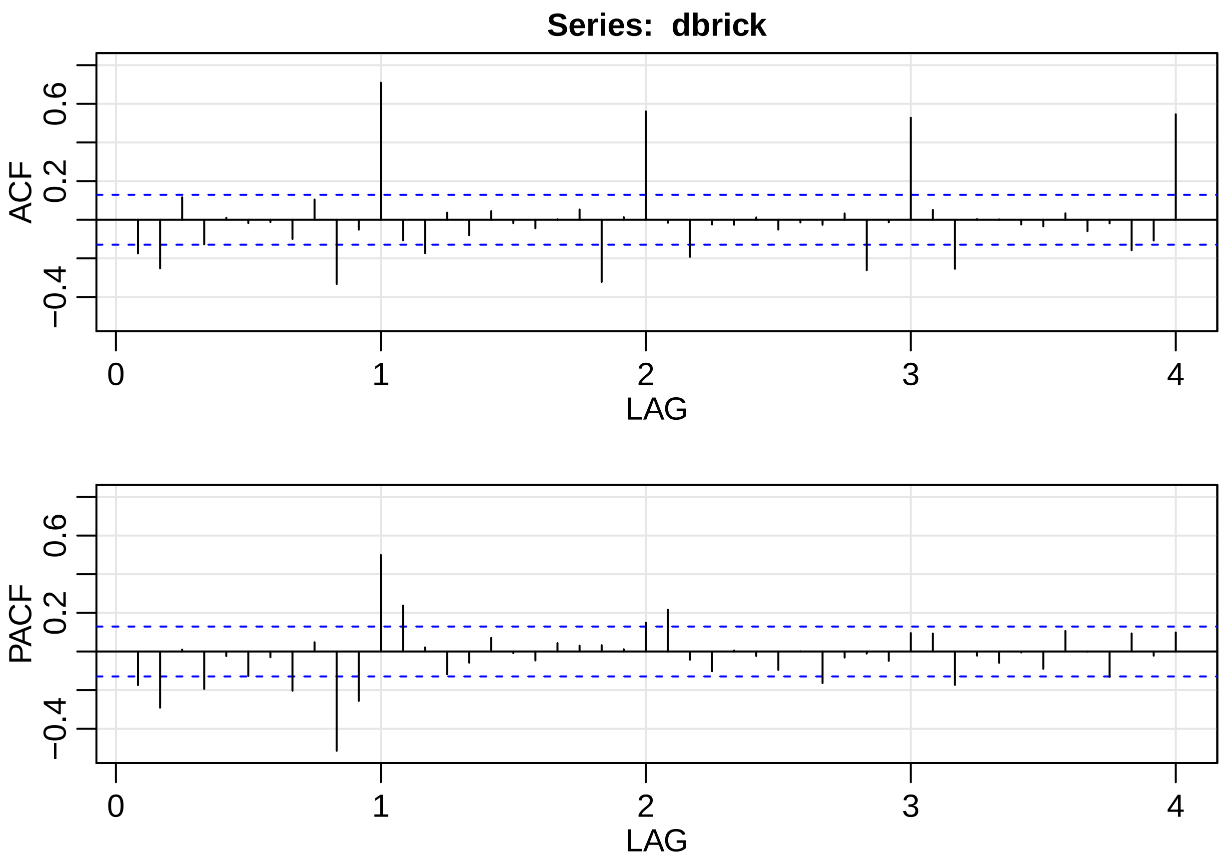



```
pacf(brick)
```



Consider stationarizing this data via first-order differenceing.

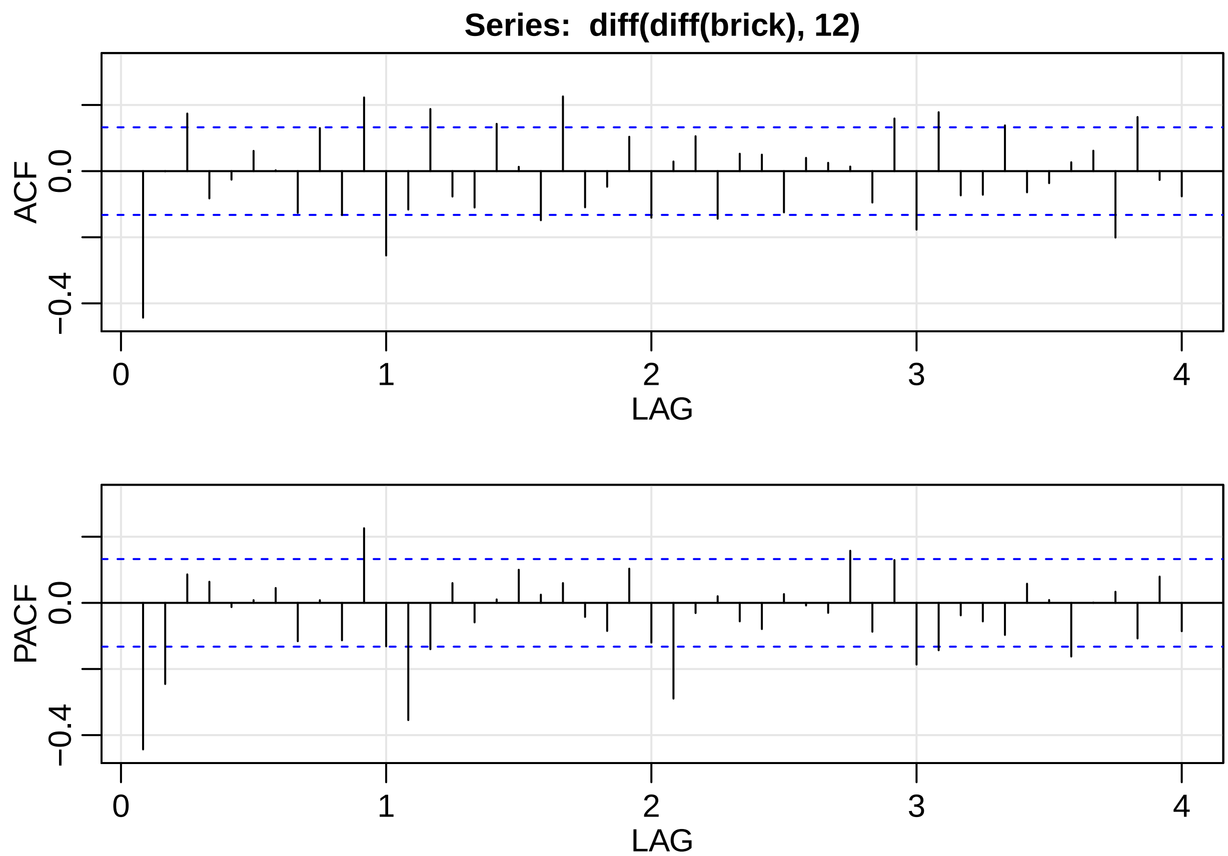
```
dbrick <- diff(brick)
acf2(dbrick,48)[1]
```




```
## [1] -0.17
```

Even with the first order of differencing applied, we observe that there is still slow residual decay in the ACF plot at a seasonal lag period of 12. This suggests that a second order difference should applied.

```
acf2(diff(diff(brick), 12), 48)[1]
```



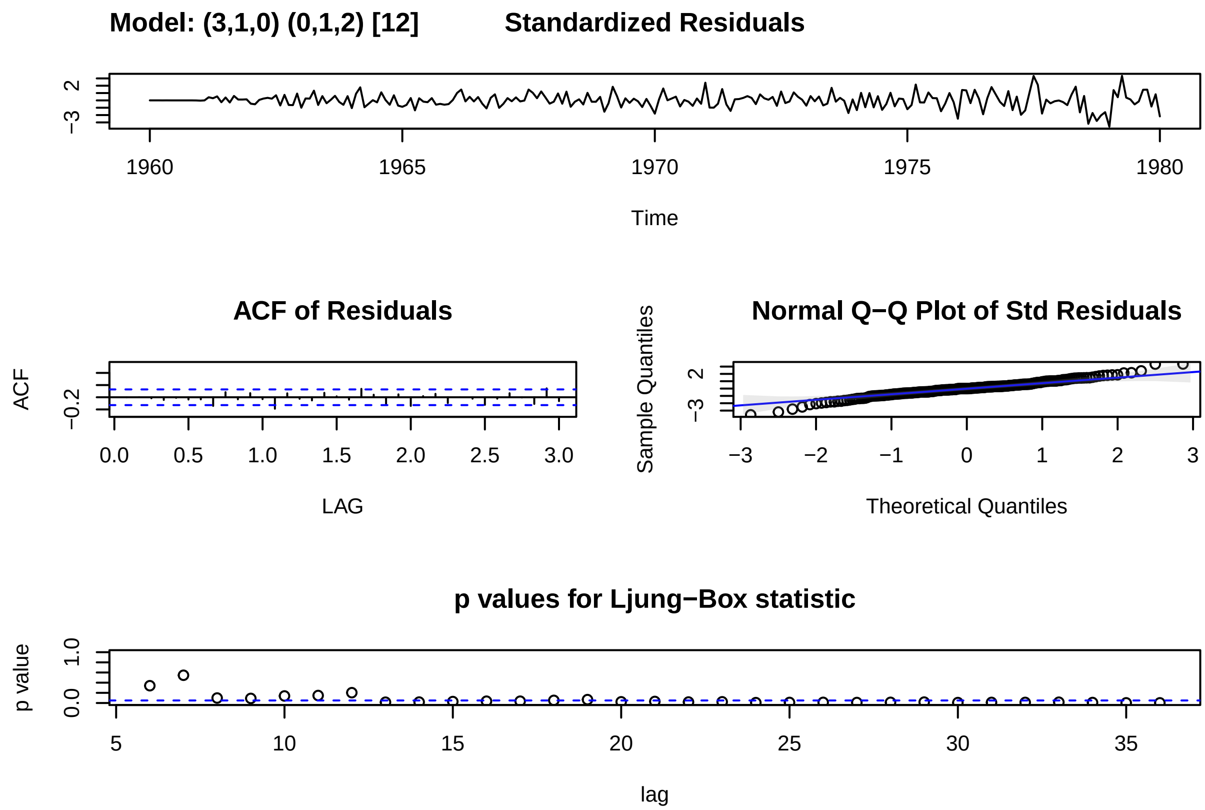

```
## [1] -0.44
```

From the seasonal lag perspective, we can see that the ACF cuts off at the 2nd seasonal lag, while the PACF appears to tail off. This would suggest a SARMA model of (0,2). Within the first seasonal cycle, it can be seen that PACF appears to be cutting off at lag = 3, while the ACF tails off. Thus a proposed model can be ARMA (3,0) x (0,2)_12 for the differenced time series.

```r
sarima(brick, 3,1,0, 0,1,2, 12)
```

```
## initial  value 2.316501
## iter   2 value 2.082344
## iter   3 value 2.018921
## iter   4 value 1.986378
## iter   5 value 1.964898
## iter   6 value 1.960672
## iter   7 value 1.959212
## iter   8 value 1.959089
## iter   9 value 1.958890
## iter  10 value 1.958870
## iter  11 value 1.958867
## iter  12 value 1.958867
## iter  12 value 1.958867
## final  value 1.958867
## converged
## initial  value 1.969522
## iter   2 value 1.969380
## iter   3 value 1.969078
```

```
## iter   4 value 1.968929
## iter   5 value 1.968904
## iter   6 value 1.968903
## iter   6 value 1.968903
## iter   6 value 1.968903
## final  value 1.968903
## converged
```




```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), include.mean = !no.constant, optim.control = list(trace = trc,
##     REPORT = 1, reltol = tol))
##
## Coefficients:
##           ar1      ar2     ar3     sma1     sma2
##       -0.5935  -0.2042  0.1479  -0.7591  -0.0367
## s.e.   0.0684   0.0762  0.0682   0.0866   0.0869
##
## sigma^2 estimated as 48.63:  log likelihood = -772.43,  aic = 1556.86
##
## $degrees_of_freedom
## [1] 223
##
## $ttable
```

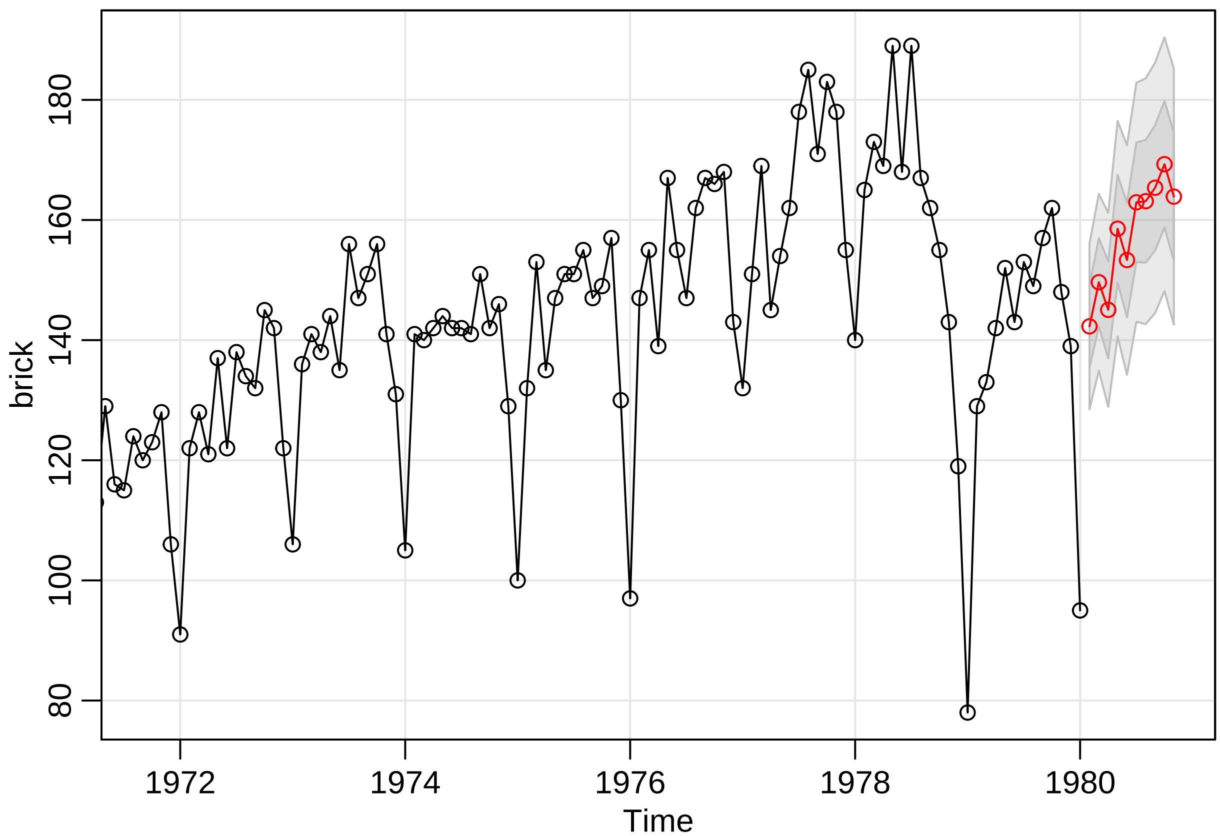
```
##      Estimate     SE t.value p.value
## ar1   -0.5935 0.0684 -8.6713  0.0000
## ar2   -0.2042 0.0762 -2.6788  0.0079
## ar3    0.1479 0.0682  2.1668  0.0313
## sma1  -0.7591 0.0866 -8.7688  0.0000
## sma2  -0.0367 0.0869 -0.4228  0.6729
##
## $AIC
## [1] 4.925686
##
## $AICc
## [1] 4.935474
##
## $BIC
## [1] 3.997985
```

Looking at the model diagnostics, we can see that the model does fit fine for earlier lags, although there might still be some outliers in the data with unexplained variance (as shown in the Normal QQ plot, and the standardised residuals).

```r
auto.arima(brick)
```

```
## Series: brick
## ARIMA(1,0,3)(0,1,2)[12] with drift
##
## Coefficients:
##          ar1      ma1     ma2     ma3     sma1     sma2   drift
##       0.8452  -0.4738  0.1683  0.1588  -0.6485  -0.1605  0.3894
## s.e.  0.0566   0.0915  0.0830  0.0910   0.0758   0.0748  0.0546
##
## sigma^2 estimated as 49.01:  log likelihood=-773.31
## AIC=1562.62   AICc=1563.27   BIC=1590.09
```

```r
sarima.for(brick, 10, 1,0,3, 0,1,2, 12)
```




```
## $pred
##           Feb      Mar      Apr      May      Jun      Jul      Aug
## 1980 142.2943 149.6362 145.0447 158.5480 153.3325 162.9443 163.1305
##           Sep      Oct      Nov
## 1980 165.3662 169.2914 163.8926
##
## $se
##            Feb       Mar       Apr       May       Jun       Jul       Aug
## 1980  6.894003  7.354126  8.070724  8.965617  9.553698  9.952536 10.227917
##            Sep       Oct       Nov
## 1980 10.420162 10.555319 10.650802
```

Conclusion

By using the method of maximum likelihood, the present study identified that the ARMA (,) model.

Currently, the use of brick has remained steady, at around seven to nine billion a year, down from the 15 billion used annually during the early 1900s. In an effort to increase demand, the brick industry continues to explore alternative markets and to improve quality and productivity. Fuel efficiency has also improved, and by the year 2025 brick manufacturers may even be firing their brick with solar energy. However, such changes in technology will occur only if there is still a demand for brick.

Along with the predicted data, there is the prediction bounds (+- 1 standard error represented by the darker gray bands and +-2 standard errors boundaries represented by the lighter gray bands). As the time progresses beyond the first predicted point, the uncertainty increases and thus the prediction boundaries increase in amplitude.

References

"'Brick Manufacturing from Past to Present'." 1990. *The American Ceramic Society Bulletin*, May, 807–13.

"'Clay Brick Association of South Africa'." n.d. www.claybrick.org.

"'Trends in Brick Plant Operations'." 1992. *The American Ceramic Society Bulletin*, 69–74.

"'Wienerberger Clay Building Materials Europe'." n.d. https://clay-wienerberger.com.