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A Comparison Of The Bayesian Structural Time Series Technique With The Autoregressive Integrated Moving Average Model For Forecasting

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ABSTRACT

In this work, two forecasting models, Bayesian Structural Time Series (BSTS) and Autoregressive Integrated Moving Average (ARIMA), were used to estimate Turkish coal production from 1970 to 2022 which obtained through the World Bank database. The main objective was to evaluate these models' predictive accuracy for trends in coal production. The modeling and analytic procedures were carried out using the R program, and MAE, RMSE, R^2 and MAPE were also used for this comparison in order to guarantee accurate and thorough results. The results showed that when it came to estimating the time series data of coal production in Turkey, the BSTS model outperformed the ARIMA model. When compared to the Box-Jenkins approach of the ARIMA model, the BSTS model's which takes into account the inherent uncertainties and complexities in coal production showed superior accuracy and reliability.

Keywords: *Forecasting, Bayesian Structural Time Series, Autoregressive Integrated Moving Average, Coal Production.*

1. Introduction

Forecasting complex systems is a critical component of current data analysis and processing science. Forecasting with time series data is one of the most studied and investigated disciplines. Time series data depict the dynamic behavior and cause-and-effect interactions of the key processes in a complex system, and they offer the foundation for forecasting and understanding the system's growth. Most forecasting approaches, however, rely on linear and stationary process models (Kalinina, I. and Gozhyj, A., 2022). The Bayesian technique is one strategy for dealing with nonlinear and nonstationary data (Navas Thorakkattle, M., et. al, 2022).

E. Harvey 1990, introduced the Bayesian structural time series (BSTS) model as a structural time series theory. Unlike typical statistical ARIMA models, structural time series models include unobservable elements such as trends and seasonality components. Furthermore, models may easily be expanded to incorporate explanatory factors and work with multivariate time series. In the study of time series in the situation of missing data, state-space models and techniques and recursive equations employing the Kalman filter are applied. State-space models are based on Markov processes since each state is dependent on the preceding one. As a result, the future state is estimated based on the present (Kalman, R.E., 1960). For posterior distribution modeling, the structural time series model employs the Markov Chain Monte Carlo (MCMC) sampling process, which smoothes predictions

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derived from a large number of plausible underlying models. The MCMC technique using the Gibbs algorithm restricts preselection; it must be combined with probability or the Metropolis-Hastings algorithm to accelerate convergence in multivariate models (Fragoso, et. al., 2018).

The study's initial purpose is to create BSTS models for analyzing future Turkish coal production patterns and comparing their prediction power to that of the most regularly used ARIMA models. To achieve this purpose, we investigated BSTS models and conducted intervention analysis using Bayesian structural time series models. When compared to ARIMA models, the results indicated greater levels of accuracy. The proposed approaches may be used to investigate these tendencies in any other prediction process.

2. LITERATURE REVIEW

Ticknor, 2013 presents a new approach to financial market behavior prediction that incorporates a Bayesian regularized artificial neural network. The aim of this study is to forecast the closing price of individual stocks in the future by utilizing financial technical indicators and daily market prices as input variables. In financial time series analysis, predicting stock price fluctuations is a difficult undertaking, but successful forecasts can help investors improve their stock returns. The Bayesian regularized artificial neural network is highlighted in the study's conclusion as a potential technique for stock price prediction. With the addition of a probabilistic method and a reduction in model complexity, the suggested model shows promise in improving stock price forecast accuracy. Consequently, this can help investors make knowledgeable selections in the financial markets. Pinilla et al. (2018) used a Bayesian structural time-series model in their study to evaluate the causal effect of partial and entire bans on public smoking on cigarette sales. This method offers a fresh methodology to investigate the causal impacts of policy interventions by combining a state-space model. It enables the creation of counterfactual scenarios using various control series and expands the widely used difference-in-differences approach to the time series environment. In contrast to a partial ban, the study emphasizes the benefits of using this methodology to calculate the effectiveness of an outright ban on smoking in public areas. Fattah et al. (2018) used the autoregressive integrated moving average (ARIMA) model to forecast demand in a food industry. The study used a time series technique with the goal of improving demand modeling and forecasting. The study demonstrated how demand history may be used to forecast future demand and the supply chain's ensuing effects. Using the historical demand data, the researchers created many ARIMA models by applying the Box-Jenkins time series process. Four performance criteria, the Akaike criterion, the Schwarz Bayesian criterion, maximum likelihood, and standard error, were used to choose the best model. Further validation of the selected model, ARIMA (1, 0, 1), was conducted under the same conditions using additional historical demand data. The study's findings proved how successful the ARIMA (1, 0, 1) model is in modeling and projecting future demand for the food manufacturing business. Based on the anticipated demand, these findings provide manufacturing firm managers with trustworthy guidance to help them make judgments. Madhavan et al. (2020) did a study that centered on short-term forecasting in the Indian airline industry, with a particular focus on the air passenger and air cargo sectors. Using two models, ARIMA and BSTS, the study sought to forecast the demand for air travel and freight in India's aviation sector. The directorate general of civil aviation website provided the dataset, which comprised air passenger and cargo data for the ten-year period between 2009 and 2018. Both the BSTS and ARIMA models' dynamic performance and uncertainty incorporation capabilities were assessed. The results showed that in all four commercial aviation sectors, international passenger, domestic passenger, international air cargo, and domestic air cargo, both the ARIMA and BSTS models were suitable for short-term forecasting. The report also offered suggestions for further investigation into medium- and long-term forecasting in the Indian aviation sector. Almarashi and Khan (2020) analyzed a univariate dataset using the Bayesian Structural Time Series approach (BSTS). The study's primary objective was to analyze actual secondary data on Flying Cement's stock prices for a full year. To provide statistical results, the study used simulation techniques such the Monte Carlo Markov Chain (MCMC) and the Kalman filter. Even though the investigation focused mostly on stock prices, lead times in complicated engineering processes might be handled using the same BSTS methodology. The Autoregressive Integrated Moving Average (ARIMA) technique was also taken into consideration in the study to compare BSTS with a conventional method. The R software's BSTS package was utilized to generate Bayesian posterior sampling distributions. A real dataset was used to test four BSTS models in order to illustrate how the BSTS method functions. Mean Absolute Percentage Error (MAPE) and forecast plots were used to assess the prediction accuracy of various models. The goal of the study was to offer a simple mechanism that practitioners and researchers could simply duplicate. The results showed that both BSTS and ARIMA produced comparable results for short-term forecasting. Based on the data collected, BSTS with a local level was shown to be the most appropriate option for long-term forecasting. A study by AL-Moders and Kadhim (2021) concentrated on the use of the BSTS approach for oil price forecasting. According to the research, BSTS is the best method for predicting oil prices since it can take into account historical data and reflect observed variations over time. For nations like Iraq, which primarily depend on oil earnings, accurate estimates of oil prices are especially crucial because changes in these prices have an immediate effect on their overall economic health. As a result, it is critical to use models that can adjust to new information and offer trustworthy projections for oil prices in the future. The price of oil is predicted by the researchers to reach $156.2 by 2035, indicating a rising tendency in the future, based on their analysis using BSTS. Talkhi et al. (2021) compared different time series forecasting techniques in their study's investigation of modeling and forecasting the number of COVID-19 confirmed and death cases in Iran. Finding the most accurate model to forecast the number of confirmed and fatal cases in Iran was the study's main goal. Three measures were used to assess the performance of these models: RMSE, MAE, and MAPE. The number of confirmed and fatality cases for the following thirty days was predicted using the model deemed to be the best, which had the lowest performance metrics. Data on the total number of confirmed cases and deaths in Iran between February 20 and August 15, 2020, were used in the study. Based on the data that was available in Iran, the results showed that the BSTS model performed the best at predicting the number of confirmed cases. Conversely, the best model for forecasting mortality cases in the future was shown to be the ARIMA model. Based on these estimates, the number of new confirmed COVID-19 cases and deaths was predicted to reach 2484 on September 14, 2020. Madhavan et al. (2023) used data from the Directorate General of Civil Aviation (DGCA-India) website for a decade (2009-2018) to forecast air passenger and cargo demand in the Indian aviation industry using the autoregressive integrated moving average (ARIMA) and Bayesian structural time series (BSTS) models. They evaluated the ability of both the ARIMA and BSTS models to incorporate uncertainty in dynamic settings. Their findings suggested that, like ARIMA, BSTS is suitable for short-term forecasting of all four commercial aviation sectors.

3. MATERIAL AND METHOD

Coal production data in Turkey, spanning from 1970 to 2022, was collected from the World Bank website. A comprehensive analysis was performed on the gathered data to find and fix any missing numbers, outliers, or inconsistencies. Various data preprocessing techniques, such as imputation or removal of missing values, were employed as necessary. For comparison, two models, a Bayesian model and a classical model, were chosen. The traditional model made use of the ARIMA model, which was founded on the Box-Jenkins methodology, whilst the Bayesian model made use of the BSTS approach. For data analysis and modeling, the R program was used to guarantee reliable and thorough outcomes. By using Markov chain Monte Carlo (MCMC) sampling techniques to determine the posterior distribution, the BSTS model was implemented using Bayesian inference techniques. Appropriate prior distributions for model parameters had to be specified. The coal production time series data were integrated into the BSTS model as inputs, allowing it to capture underlying trends, seasonality, and coal production-related uncertainty. The Box-Jenkins method was followed by the ARIMA model to determine the suitable for coal production. Maximum likelihood estimation was used to estimate the model parameters, and historical trends were used to predict future values. Evaluation criteria including mean squared error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R2) were used to compare the performance and accuracy of the Bayesian and classical models. Each model's forecasts were compared to the dataset's actual coal production for the corresponding years.

4. Autoregressive Integrated Moving Average

The ARIMA model, created by Box and Jenkins (1970) and often known as the Box-Jenkins technique, is a type of time-domain model that is widely used to fit and predict time series with temporal correlation (Montgomery et al. 2016; Khalil, D.M. and Hamad S.R., 2023). The generic title for this type of ARIMA model is ARIMA(p, d, q), and it consists of three components (or terms): autoregressive (AR), integrated (or differencing), and moving average (MA) terms, each with the appropriate order of p, d, and q. Montgomery et al. (2016) found that the AR and MA terms are determined by the amount of temporal correlation in a time series, whereas the differencing term can change a nonstationary series to stationary. The ARIMA model may be extended to include seasonal fluctuations, temporal correlation in variance, and many exogenous factors. The integration of seasonal components with the ARIMA model results in a seasonal ARIMA (SARIMA) model, which was used to give future daily temperature and precipitation predictions, as explained further (Mohammed, P.A., et. al, 2022).

5. Bayesian Structural Time Series

The Bayesian Structural Time Series (BSTS) method is a statistical modeling technique applied to time series analysis and prediction. It is especially beneficial for dealing with complicated and ambiguous time series data. BSTS decomposes time series into trend, seasonality, and irregular components, and uses Bayesian inference techniques for estimate and prediction (Khidir, H.A., et. al, 2023). Structural models are considerably easier to generalize, such as covariates, and it is not difficult to handle missing data using structural models (Kadir, D., 2018; Xie, L., 2022). Time series researchers are increasingly valuing structural timer series models since they are versatile and modular, as well as statistical methods for feature selection. The model's flexibility is most likely due to the inclusion of all ARIMA models.

6.1. Application of ARIMA on Coal Production Time series

The explanation Key statistics that shed light on the patterns and fluctuations in coal production over time are shown in figure 1 for the years 1970 to 2022. This dataset, which covers Turkey's coal production in tons per year from 1970 to 2021, is a time series compilation of annual observations. 54 observations are recorded for it. This information is frequently used to look at historical trends and patterns in Turkey's coal production. It can help predict future patterns in Turkey's coal output and offer insights into the different aspects that affect coal production, such as the country's economic and environmental circumstances. The statistics shows that Turkey produced the least amount of coal over this time period in 1970, coming in at about 22.86 million tons. Conversely, the peak coal production was documented in 1986, with an estimated 48.96 million tons produced. Turkey produced an average of 29.62 million tons of coal annually for the whole period. There was a noticeable fluctuation in the output levels, as seen by the coal production standard deviation, which gauges the dispersion of the data and was roughly 5.48 million tons annually.

Figure 1: illustrates the yearly fluctuation in Turkish coal production from 1970 to 2022. There were a total of 54 observations.

Because stationarity is the primary prerequisite for developing a time series model, any non-stationarity in the data must be eliminated and turned to stationary (Khalil, D.M., 2022). Several methodologies have been explored to determine and achieve dataset stationarity. The Augmented Dickey-Fuller test will be employed in this study to determine the dataset's stationarity level. Table 1 reveals that the P value is 0.578, which is significantly more than the p-value (0.05). For this reason, the time series data can be considered to have a unit root and to be nonstationary. Here, we do the first differential and see if it is stationary. Otherwise, the second distinction is carried out. The number of differentiations, sometimes referred to as the lag term in ARIMA (p, d, q), is d. After the initial differentiation, the P-value becomes 0.012, indicating that the data series has no unit root and is stationary.

Table 1: Dickey Fuller test value results

	Dickey-Fuller value	P-value
Before Differencing	-1.9187	0.578
After Differencing	-4.1634	**0.012**

6.1.2 Selecting fitting model

After applying 40 different models which represented in appendix A to the data-set to find the best model, it is discovered that ARIMA(1,0,0) is the best model to forecast the Turkish Coal production from 1970 to 2022. The estimated model and it's parameter are statistically significant, as shown in (Table 2).

Table 2: ARIMA(**1**,**0**,**0**) Model Statistics

	Estimate	SE	T-test	P-value
AR1	0.705	0.908	75.408	0.000

As well as, the model's performance measurements are shown in (Table 3).

Table 3: ARIMA(1,0,0) Model measurements

R-squared	RMSE	MAPE	MAE	AIC
0.841	3.959	9.289	2.830	308.56

The actual and predicted values of the coal production time series are represented in (Figure 2).

Figure 2: Actual and predicted values by using ARIMA(1,0,0)

6.1.3. Checking the model (1,0,0)

In the last step of model performance testing, the Box-Pierce test is used to confirm the appropriate user model, and the residual autocorrelation test is used to determine whether there is any autocorrelation (Kadir, D., 2020). The Box-Pierce value is 10.824, and the p-value for this test is 0.475, which is significantly more than 0.05, indicating that the residuals are autocorrelation-free and so white noise. As a result, it is concluded that the model ARIMA(1,0,0) is the best match for the gold price dataset, having passed model building diagnostic tests.

6.2. Using BSTS to Forecasting the Coal Production Dataset

A BSTS model divides a time series into four different components: trend, seasonality, regression, and error. The trend component accounts for the long-term trends and changes seen in the time series, whereas the seasonality component captures the repeating variations that occur at regular periods. The regression component models the relationship between the time series and extra predictor factors, and the error component depicts the random changes in the data, as seen in Figure 3.

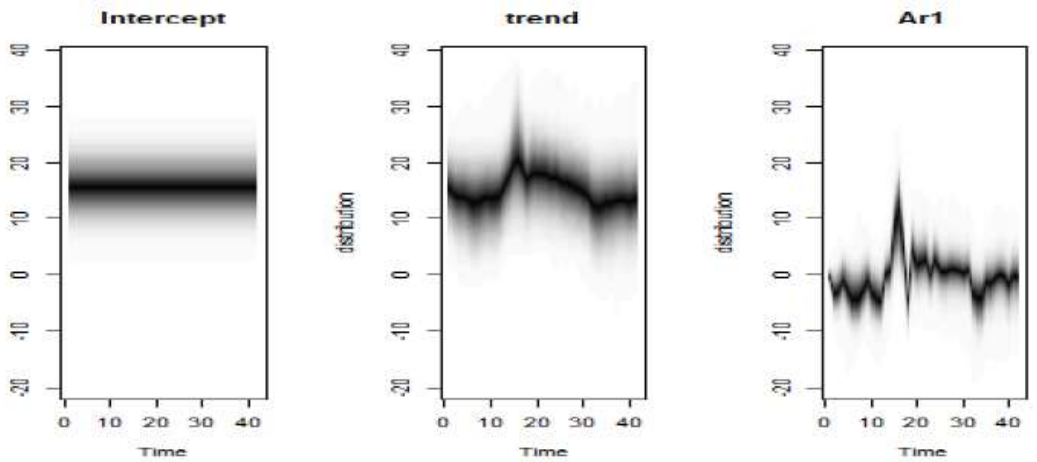

Figure3: Components of the BSTS Model

The BSTS model's prediction errors are calculated after a 10-iteration burn-in phase. These mistakes provide useful information about the model's performance at various time periods. The burn-in period, which is often employed in Bayesian modeling, entails discarding the early iterations of the MCMC algorithm. This improves the algorithm's ability to search the parameter space and arrive at the correct posterior distribution. When examining prediction errors during the burn-in phase, it is critical to account for the uncertainty associated with the estimated model parameters. The burn-in duration was chosen to balance computational efficiency and precise parameter estimation.

6.2.1. Select fitting model

Based on Figure 4, these values indicate that the model is well-suited to collecting data patterns. As a result, it may be used to accurately predict the model's parameters.

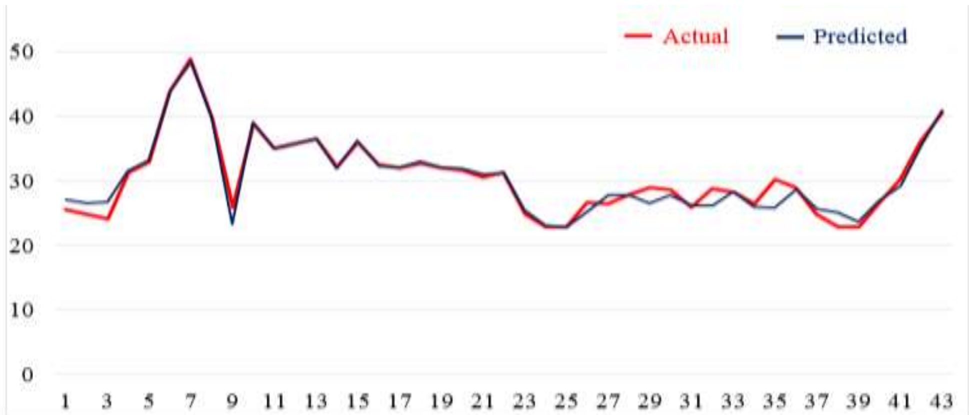

Figure 4: Predicted and actual values of coal production time series using BSTS.

The residual standard deviation (1.4173) of the model indicates the difference between anticipated and observed values. A larger score implies a bigger difference between projections and actual data. The standard deviation of the anticipated values (7.06381) reflects the model's forecasting uncertainties. A higher number implies greater uncertainty in projecting future values. The coefficient of determination (0.913) is the proportion of variation in the observed data that can be explained by the model. A greater score implies a better fit, implying that the model accounts for a considerable percentage of the variability in the data. The relative goodness-of-fit (-1.10327) statistic compares the data's actual log-likelihood to the model's anticipated log-likelihood. A negative number indicates that the BSTS model fits better than the null model. Overall, these output metrics show that the BSTS model fits the data well and depicts the underlying dependency structure of the time series. During the fitting procedure, the model parameters are estimated using Bayesian inference and the MCMC technique. Running additional iterations typically results in more accurate parameter estimations. The given output is a progress report, including iteration numbers and timestamps indicating algorithm convergence and model estimation success. Table 4 provides an evaluation of the correctness of the BSTS model.

Table 4: BSTS model assessment measures

R-squared	RMSE	MAPE	MAE
0.913	2.864	7.197	2.318

6.2.2 Model checking

After identifying and estimating the BSTS model, it was critical to determine how well it suited the data. This key phase in the model diagnostic procedure entailed assessing both the model's parameters and residuals. The residuals of the BSTS model were examined using autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, as shown in Figure 5, and all ACF and PACF values were statistically significant at the 95% confidence level. This implies that the residuals have random white noise properties, confirming that the model is appropriate for the current data. The Box-Ljung test, a statistical test designed to assess the presence of autocorrelation in the residuals of a time series model, was applied to the BSTS model's residuals based on the given output. The calculated p-value of 0.847 exceeded the threshold of 0.05. This means that inadequate evidence exists to justify the presence of autocorrelation in the model's residuals. As a result, we may infer that the model adequately describes the data's autocorrelation structure.

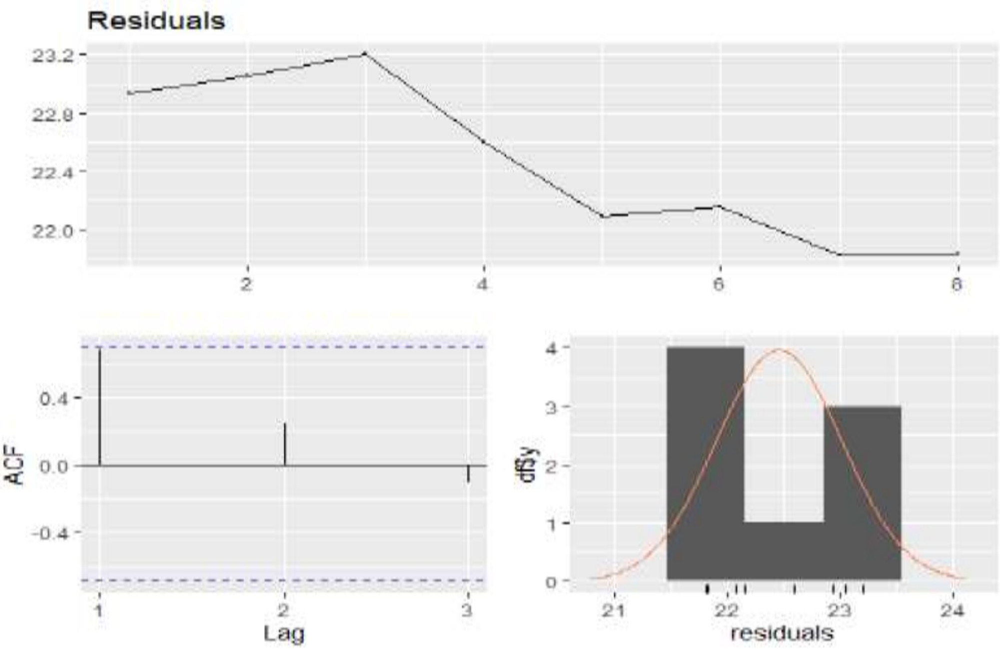

Figure 5: ACF and distribution of residuals for the BSTS model.

7. Comparison of ARIMA and BSTS Results

The results of applying the BSTS and ARIMA models for predicting Turkish coal production were compared to see whether model performed better. The BSTS models outperform ARIMA models in terms of goodness of fit. Furthermore, the RMSE values of the BSTS models in this study are much lower than those of the ARIMA models, implying that the BSTS models have a reduced error rate. When comparing their MAE values, the BSTS models fit better than the ARIMA models. Table 7 shows that when both models are employed for prediction, the BSTS models outperform the ARIMA models in terms of accuracy and error.

Table 7: Comparison of the BSTS and ARIMA

Model	MAPE	RMSE	MAE	R^2
BSTS	7.197	2.864	2.318	0.913
ARIMA(1,0,0)	9.289	3.959	2.830	0.841

8. Conclusions

The study's findings after comparing the two models reveal that the, the BSTS model is more flexible and capable of handling complicated time series patterns. It may account for both short-term and long-term trends, seasonality, and other pertinent elements. Furthermore, its Bayesian framework allows for a broader understanding of uncertainty and the inclusion of previous information. ARIMA models, on the other hand, are easier to develop and better suited to data with distinct patterns and straightforward relationships. They also give valuable diagnostic tools for examining residuals and determining model appropriateness. Finally, the decision between the BSTS and ARIMA models is determined by the unique properties of the time series data as well as the forecasting aims. When deciding which model to use, consider the complexity and type of the data, the existence of patterns and seasonality, and the availability of past knowledge.

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Appendix A: Estimated ARIMA Models with their AIC

Model		AIC	Model		AIC
ARIMA(0,0,1)	with zero mean	464.772	ARIMA(2,0,0)	with zero mean	Inf
ARIMA(0,0,1)	with non-zero mean	317.381	ARIMA(2,0,0)	with non-zero mean	310.620
ARIMA(0,0,2)	with zero mean	423.912	ARIMA(2,0,1)	with zero mean	Inf
ARIMA(0,0,2)	with non-zero mean	313.789	ARIMA(2,0,1)	with non-zero mean	312.969

ARIMA(0,0,3)	with zero mean	401.147	ARIMA(2,0,2)	with zero mean	Inf
ARIMA(0,0,3)	with non-zero mean	314.058	ARIMA(2,0,2)	with non-zero mean	315.504
ARIMA(0,0,4)	with zero mean	384.891	ARIMA(2,0,3)	with zero mean	Inf
ARIMA(0,0,4)	with non-zero mean	315.312	ARIMA(2,0,3)	with non-zero mean	318.101
ARIMA(0,0,5)	with zero mean	373.327	ARIMA(3,0,0)	with zero mean	Inf
ARIMA(0,0,5)	with non-zero mean	317.959	ARIMA(3,0,0)	with non-zero mean	313.013
ARIMA(1,0,0)	with zero mean	Inf	ARIMA(3,0,1)	with zero mean	Inf
ARIMA(1,0,0)	with non-zero mean	309.036	ARIMA(3,0,1)	with non-zero mean	315.502
ARIMA(1,0,1)	with zero mean	Inf	ARIMA(3,0,2)	with zero mean	Inf
ARIMA(1,0,1)	with non-zero mean	310.565	ARIMA(3,0,2)	with non-zero mean	Inf
ARIMA(1,0,2)	with zero mean	Inf	ARIMA(4,0,0)	with zero mean	Inf
ARIMA(1,0,2)	with non-zero mean	312.981	ARIMA(4,0,0)	with non-zero mean	315.465
ARIMA(1,0,3)	with zero mean	Inf	ARIMA(4,0,1)	with zero mean	Inf
ARIMA(1,0,3)	with non-zero mean	315.455	ARIMA(4,0,1)	with non-zero mean	318.101
ARIMA(1,0,4)	with zero mean	Inf	ARIMA(5,0,0)	with zero mean	Inf
ARIMA(1,0,4)	with non-zero mean	317.959	ARIMA(5,0,0)	with non-zero mean	318.074