FORECASTING FLUCTUATIONS OF ASPHALT CEMENT PRICE INDEX IN GEORGIA

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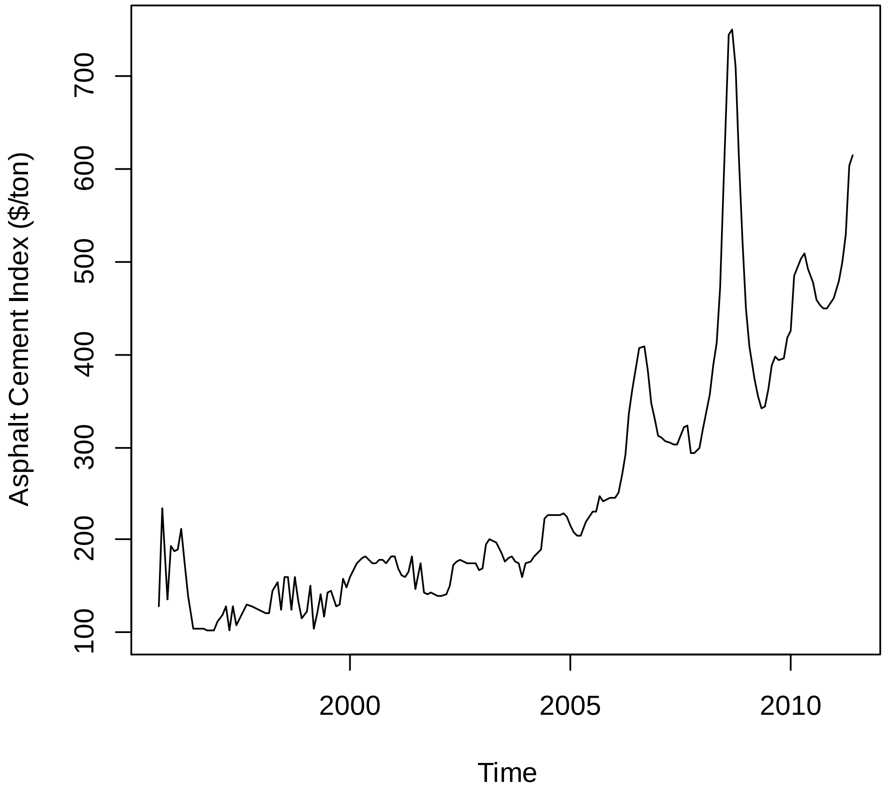
Overview

- Introduction
  - Asphalt cement price index
  - Problems related to asphalt cement price variation
- Research Objective
- Research Background
- Research Approach
  - Univariate time series forecasting models
- Summary of Results
  - In sample fitting models
  - Out of sample forecasting
- Conclusion
- Limitations and Future Works

Introduction

Introduction

Asphalt Cement Price Index in Georgia from 1995 to 2012



Research Motivation

Overall Problem

Significant volatility in the cost of Asphalt Cement leads to uncertainty about transportation project cost

Price Volatility → Uncertain Estimation

Uncertain Estimation → Problems for Owners

Uncertain Estimation → Problem for Contractors

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Research Motivation

- Related Issues to Owner Organizations
  - Hidden price contingencies
  - Very short-term price guarantees
  - Not enough bidders
- Related Issues to Contractors
  - Bid loss due to cost overestimation
  - Profit loss due to cost underestimation

Research Objective

Objective

Create appropriate univariate time series models for estimating and forecasting fluctuations in asphalt cement price index.

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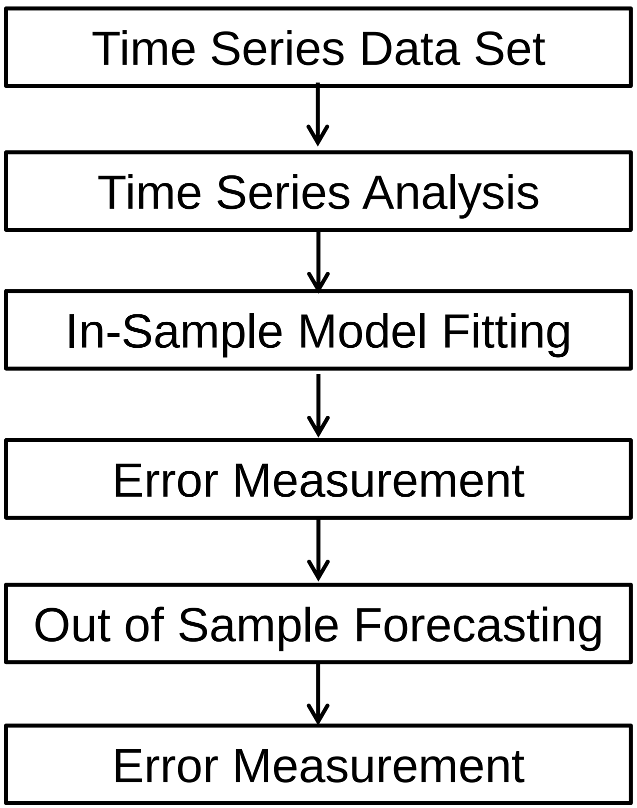
Research Background

- Forecasting Models
  - Causal Methods
    - Predicted variable is determined by independent explanatory variables
      - Regression Models
  - Pattern Analysis Methods
    - Predicted variable is determined by its historical behaviors
      - Time Series Models

Research Approach: Time Series Models



Time Series Forecasting Process

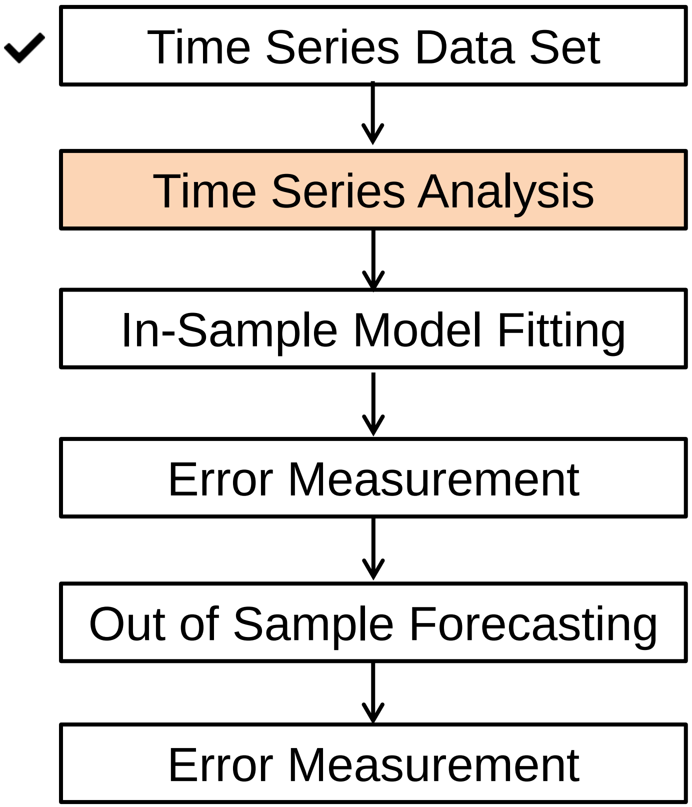
Time Series Data Set
↓
Time Series Analysis
↓
In-Sample Model Fitting
↓
Error Measurement
↓
Out of Sample Forecasting
↓
Error Measurement

A time series is a set of data points which are recorded at uniform time intervals.

In this research, our time series data set consists of monthly asphalt cement price index in the state of Georgia from Sep 1995 to June 2012

GDOT determines the index based on the average of prices from around 20 different suppliers after removing the minimum and maximum prices.

Time Series Forecasting Process



Time series analysis methods are used to extract meaningful characteristics of a time series data set

Time Series Forecasting Process

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- ↓
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- ↓
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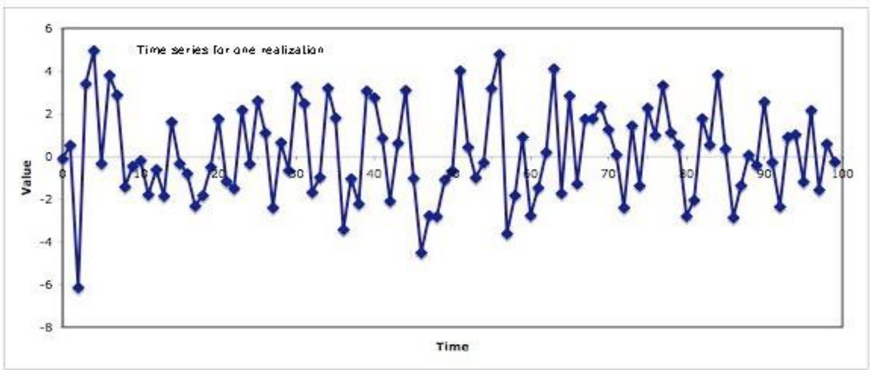
Stationary:

A time series is stationary if its statistical properties do not depend on time.



Time Series Forecasting Process

✓ Time Series Data Set

↓

Time Series Analysis

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In-Sample Model Fitting

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Out of Sample Forecasting

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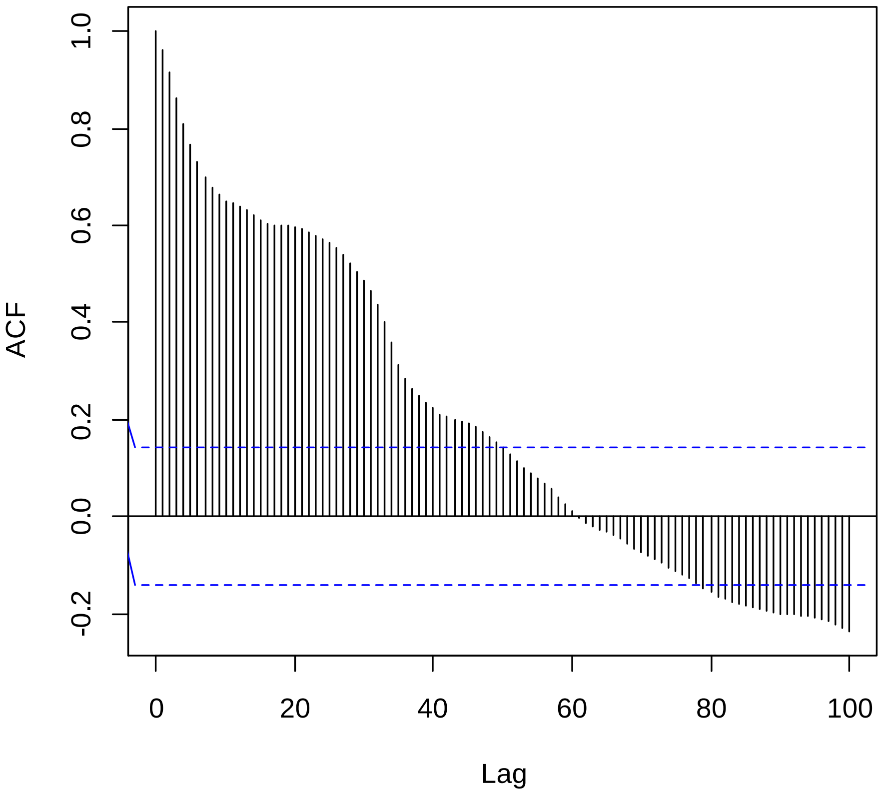
Error Measurement

Stationary: ✗

Auto Correlation Function Plot:



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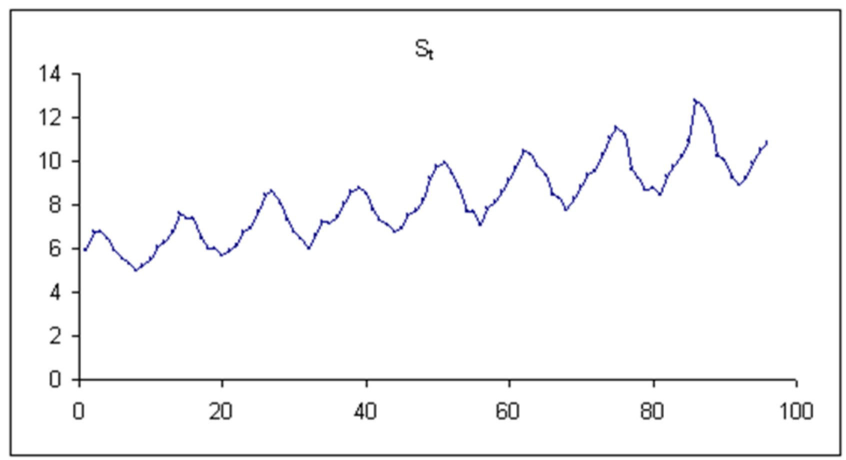
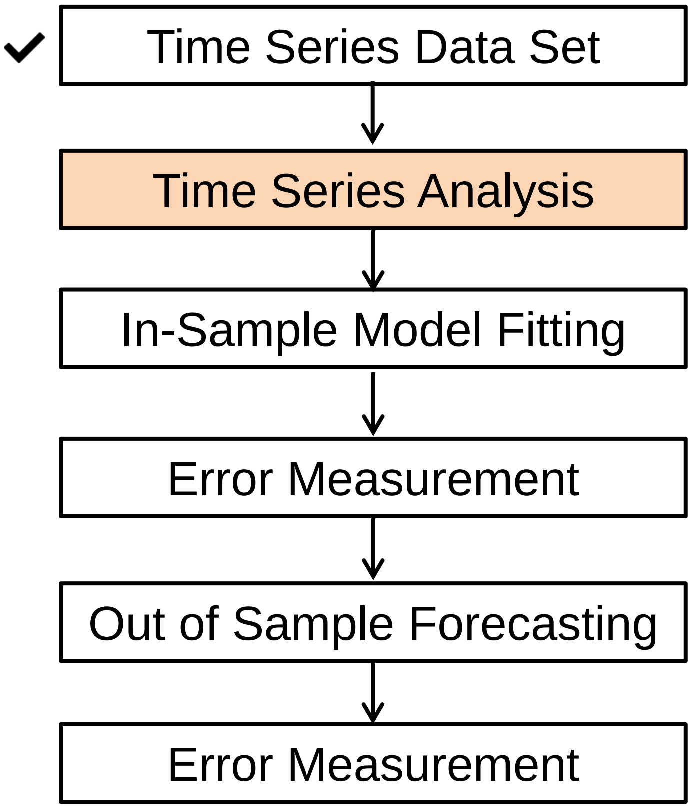
Seasonality:

Seasonality displays certain cyclical or periodic behaviors during the time.

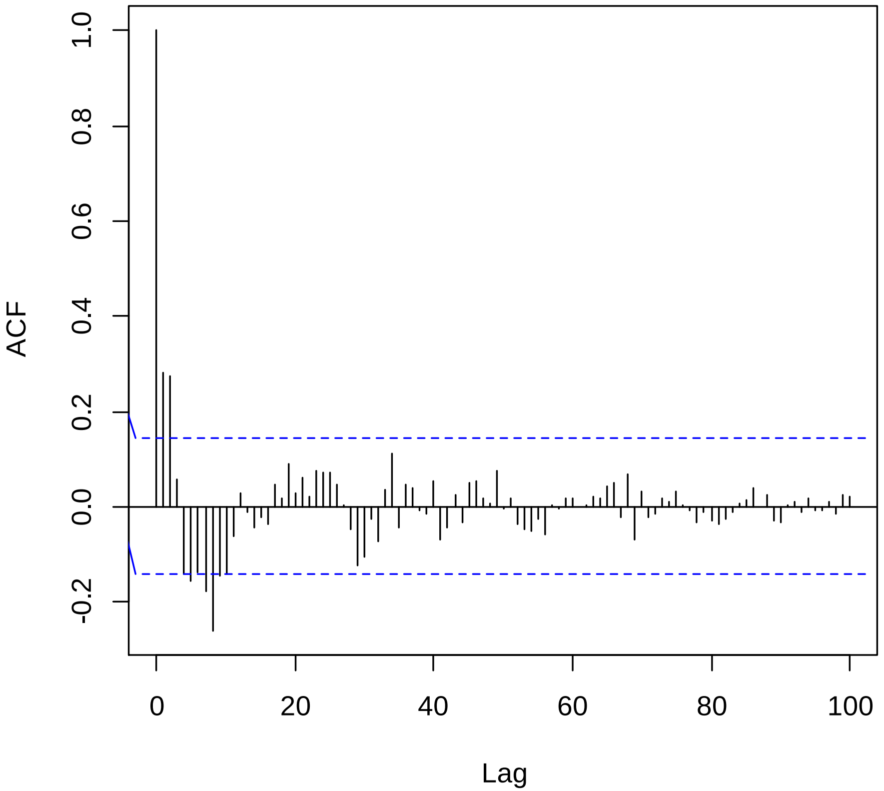


Time Series Forecasting Process



Seasonality: ✓

First Difference Auto Correlation Function Plot:



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In-sample model fitting uses historical data set to estimate parameters of the model and fit the model with actual data.

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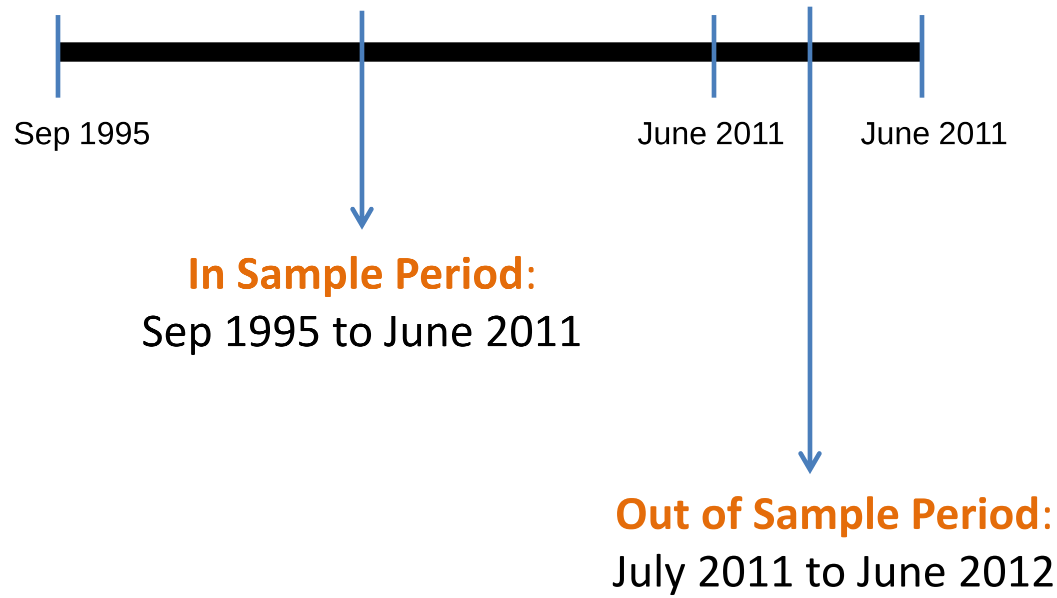

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Models:

- Simple Moving Average (SMA)
- Holt Exponential Smoothing
- Holt-Winters Exponential Smoothing
- ARIMA
- Seasonal ARIMA

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Time Series Models

Modeling Assumptions:

Time Series Methodologies	Modeling Assumptions
Simple Moving-Average (SMA)	N.A.
Holt Exponential Smoothing (Holt ES)	Underlying data show trends
Holt-Winters Exponential Smoothing (Holt-Winters ES)	Underlying data show trends & seasonality
Auto-Regressive Integrated Moving-Average (ARIMA)	Underlying data are nonstationary Model residuals are white noise
Seasonal ARIMA	Underlying data are nonstationary & seasonal Model residuals are white noise

Time Series Models

Modeling Parameters:

Time Series Methodologies	Modeling Parameters
Simple Moving-Average (SMA)	N.A.
Holt Exponential Smoothing (Holt ES)	α β
Holt-Winters Exponential Smoothing (Holt-Winters ES)	α β γ
Auto-Regressive Integrated Moving-Average (ARIMA)	p d q
Seasonal ARIMA	p d q P D Q

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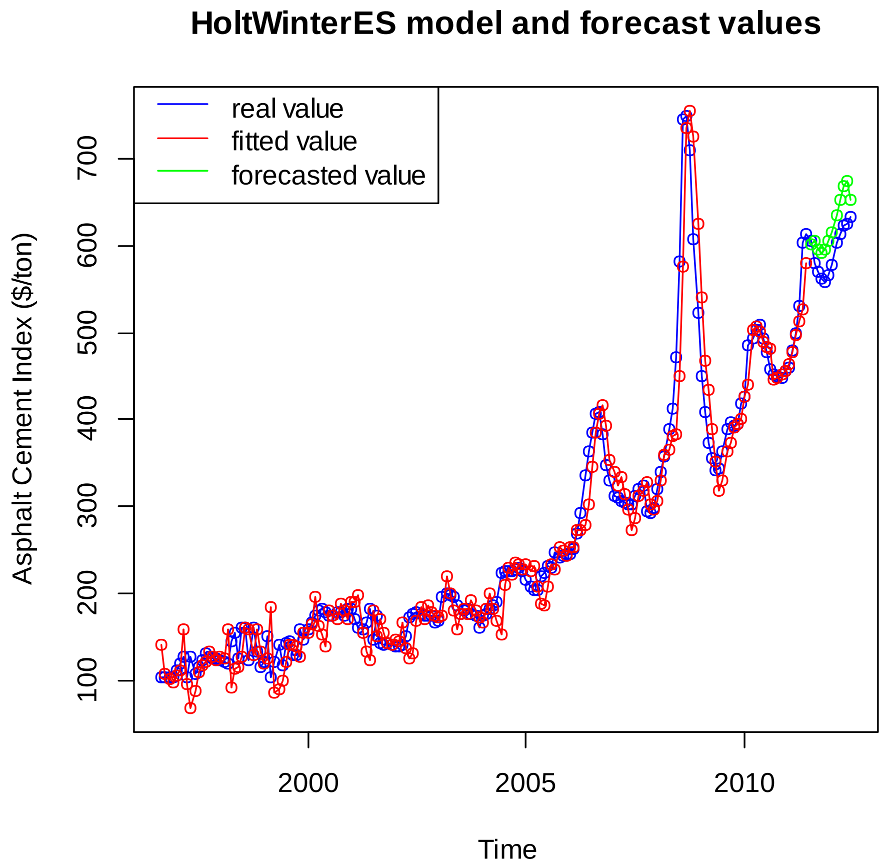

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Error Measures:

- Mean Absolute Percentage Error (MAPE)

$$\text{MAPE}=\frac{1}{N}\sum_{t=1}^{N}\frac{\left|\hat{Y}(t)-\tilde{Y}(t)\right|}{\tilde{Y}(t)}\times 100\%$$

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Error Measures:

- Mean Absolute Percentage Error (MAPE)
- Mean Square Error (MSE)

$$\text{MAPE}=\frac{1}{N}\sum_{t=1}^{N}\frac{\left|\hat{Y}(t)-\tilde{Y}(t)\right|}{\tilde{Y}(t)}\times 100\%$$

$$\text{MSE}=\frac{1}{N}\sum_{t=1}^{N}\left(\hat{Y}(t)-\tilde{Y}(t)\right)^{2}$$

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Error Measures:

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- Mean Absolute Error (MAE)

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$$MSE=\frac{1}{N}\sum_{t=1}^{N}\left(\hat{Y}(t)-\tilde{Y}(t)\right)^2$$

$$MAE=\frac{1}{N}\sum_{t=1}^{N}\left|\hat{Y}(t)-\tilde{Y}(t)\right|$$

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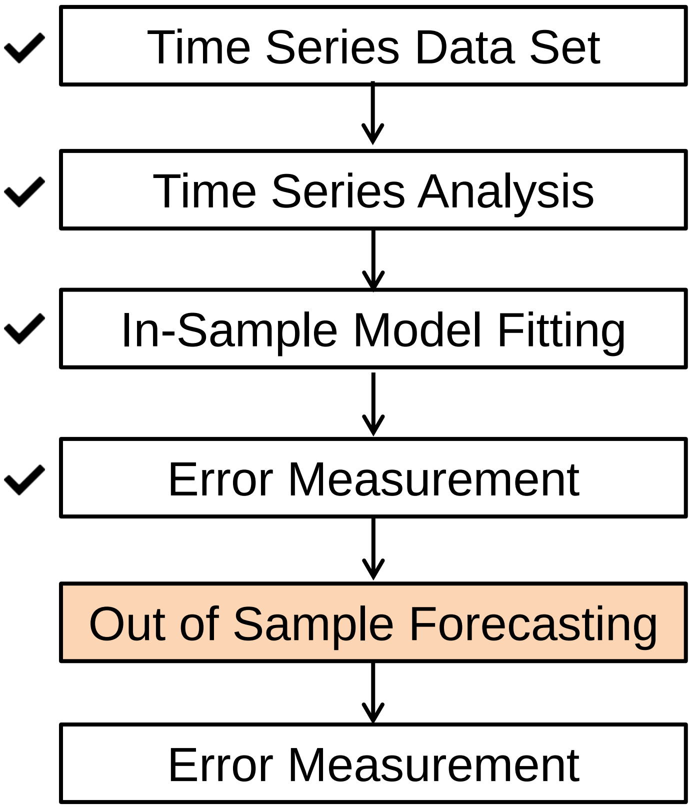
In Sample Model Fitting Error:

	SMA	ARIMA	Seasonal ARIMA	Holt ES	Holt Winters ES
MAPE	6.97%	6.91%	7.06%	8.24%	10.53%
MSE	744.91	671.15	615.75	850.38	1080.70
MAE	16.19	14.84	14.78	17.19	21.39

Time Series Forecasting Process



Out-of-sample forecasting attempts to forecast future values of a variable by using the time series models and their parameters that were determined via in-sample model fitting based on the historical data.

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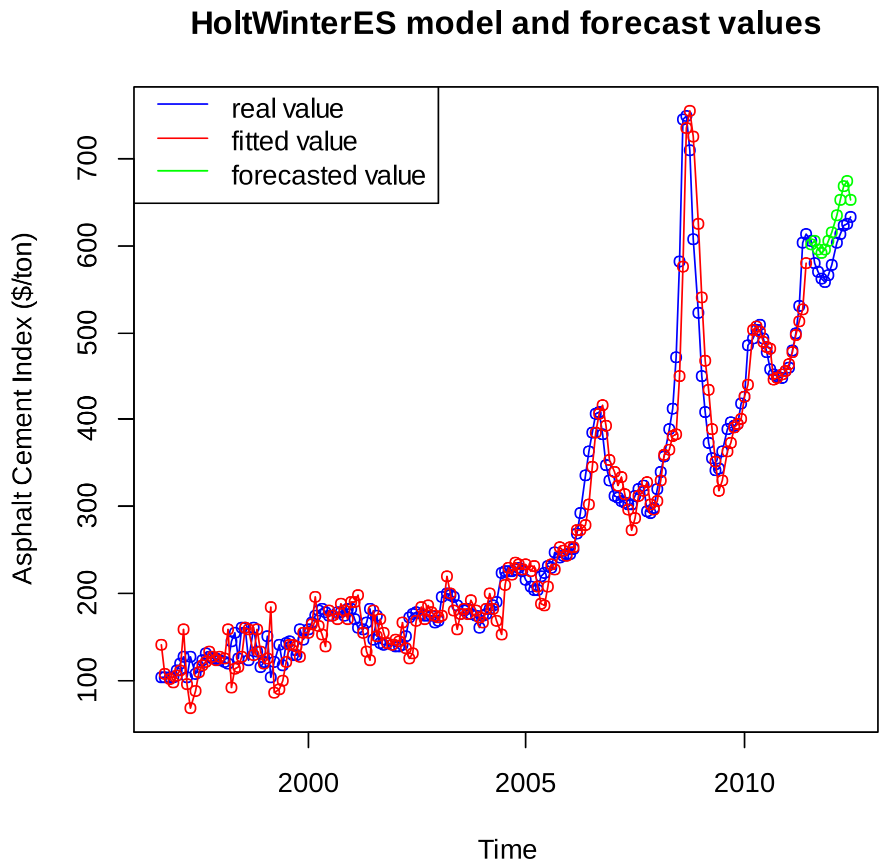

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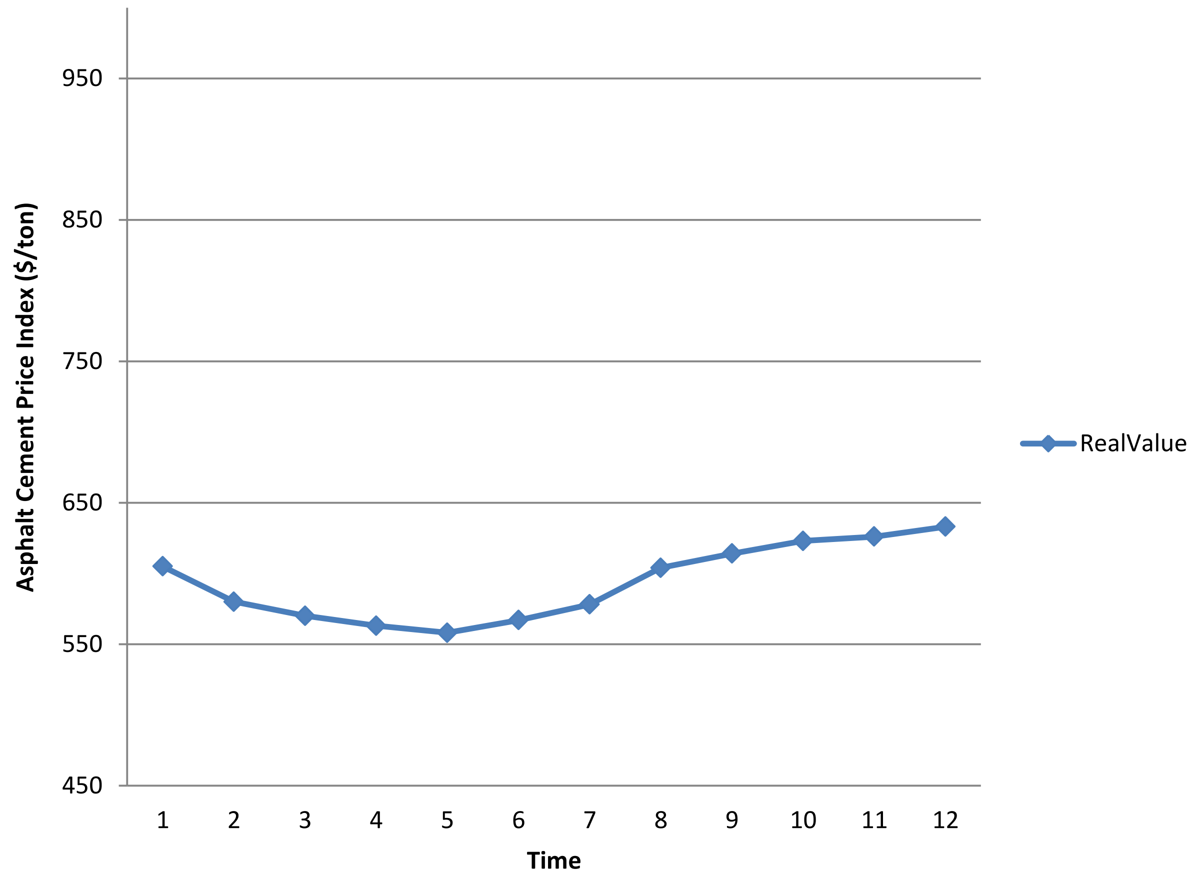
Forecasting Error

Error Measures	SMA	ARIMA	Seasonal ARIMA	Holt ES	Holt Winters ES
MAPE	4.73%	6.52%	10.03%	35.15%	5.3%
MSE	1091.75	2029.44	5845.04	51364.11	1157.18
MAE	28.90	37.97	65.65	255.75	34.47

Results: Forecasted Values



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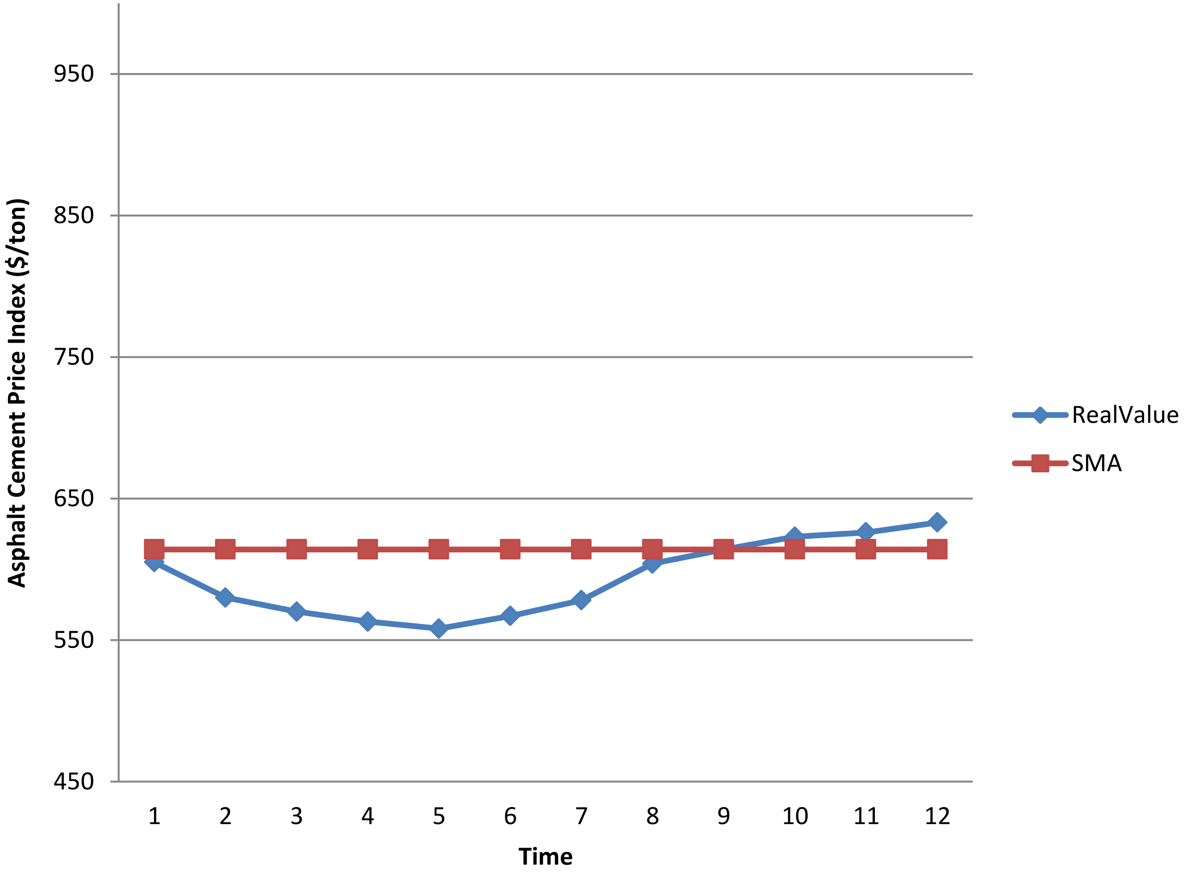

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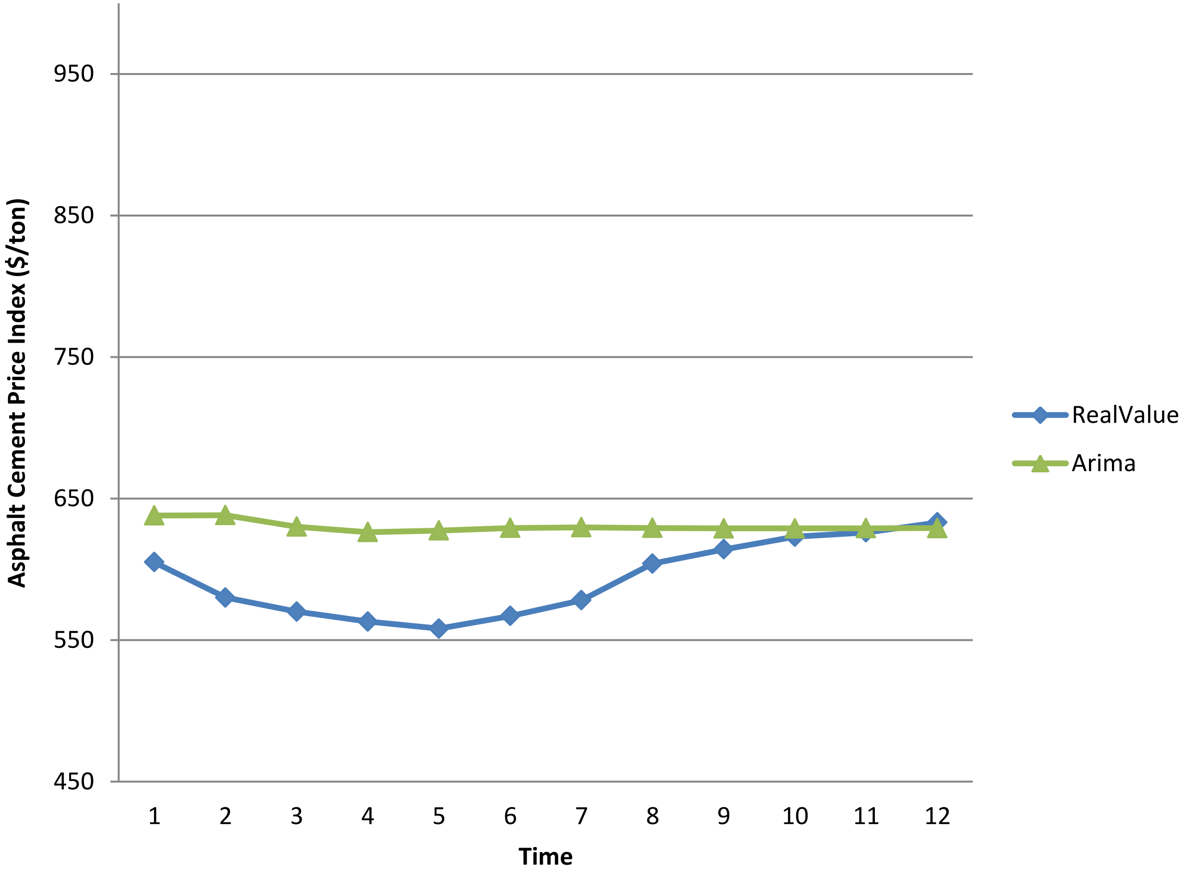

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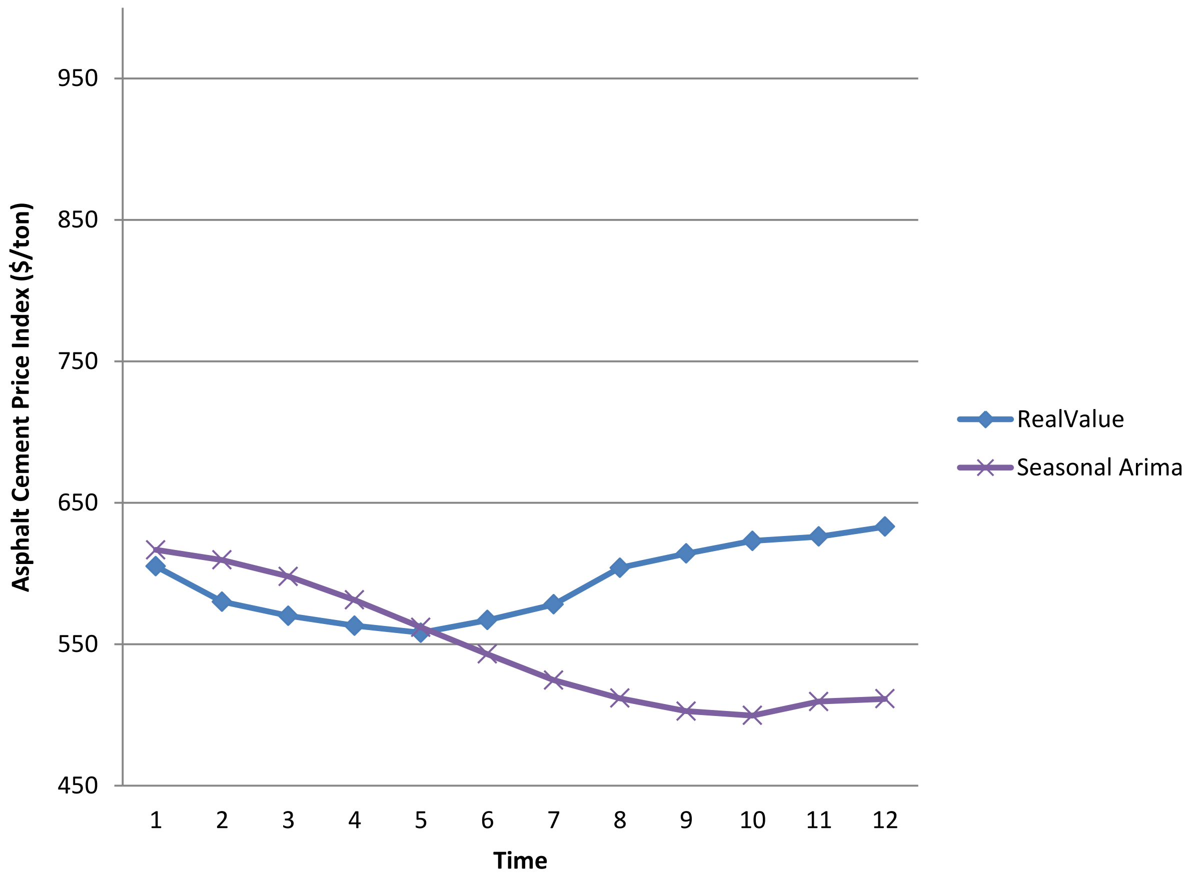

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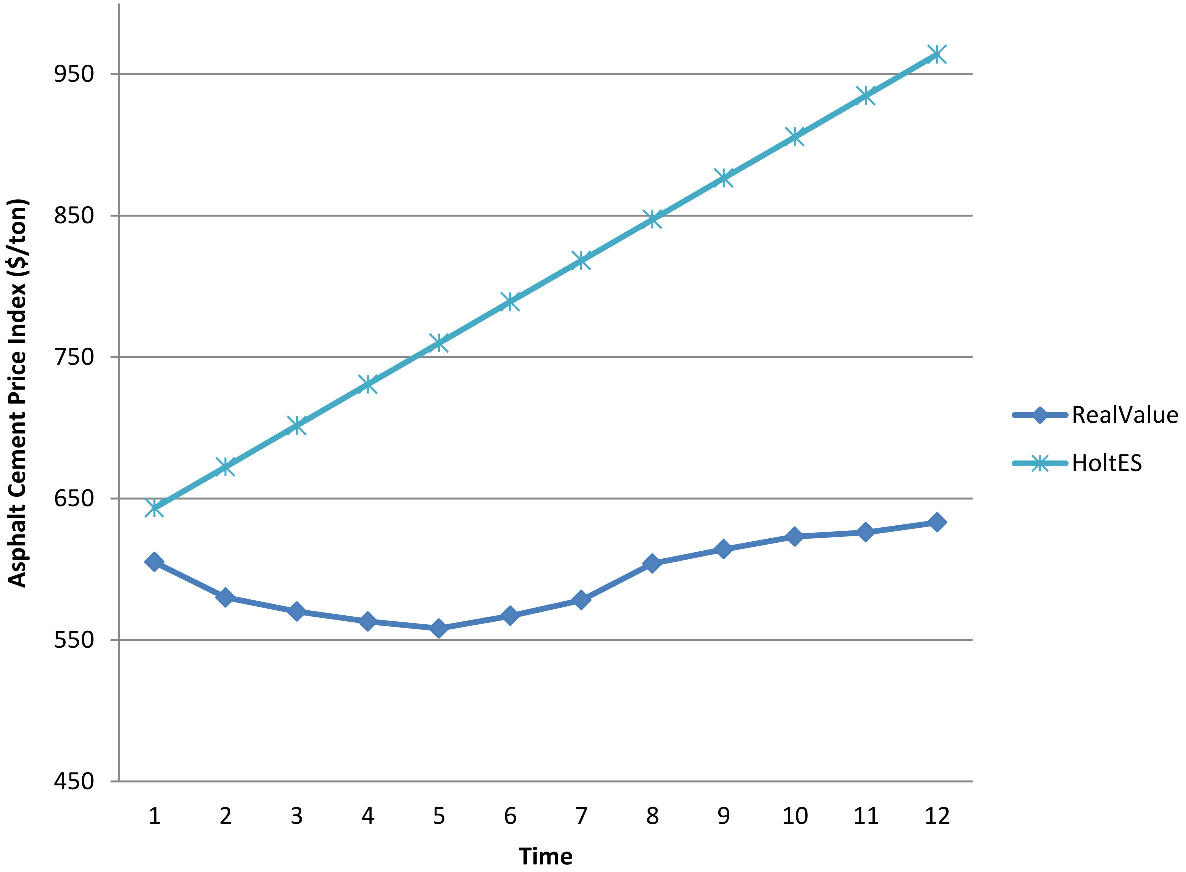
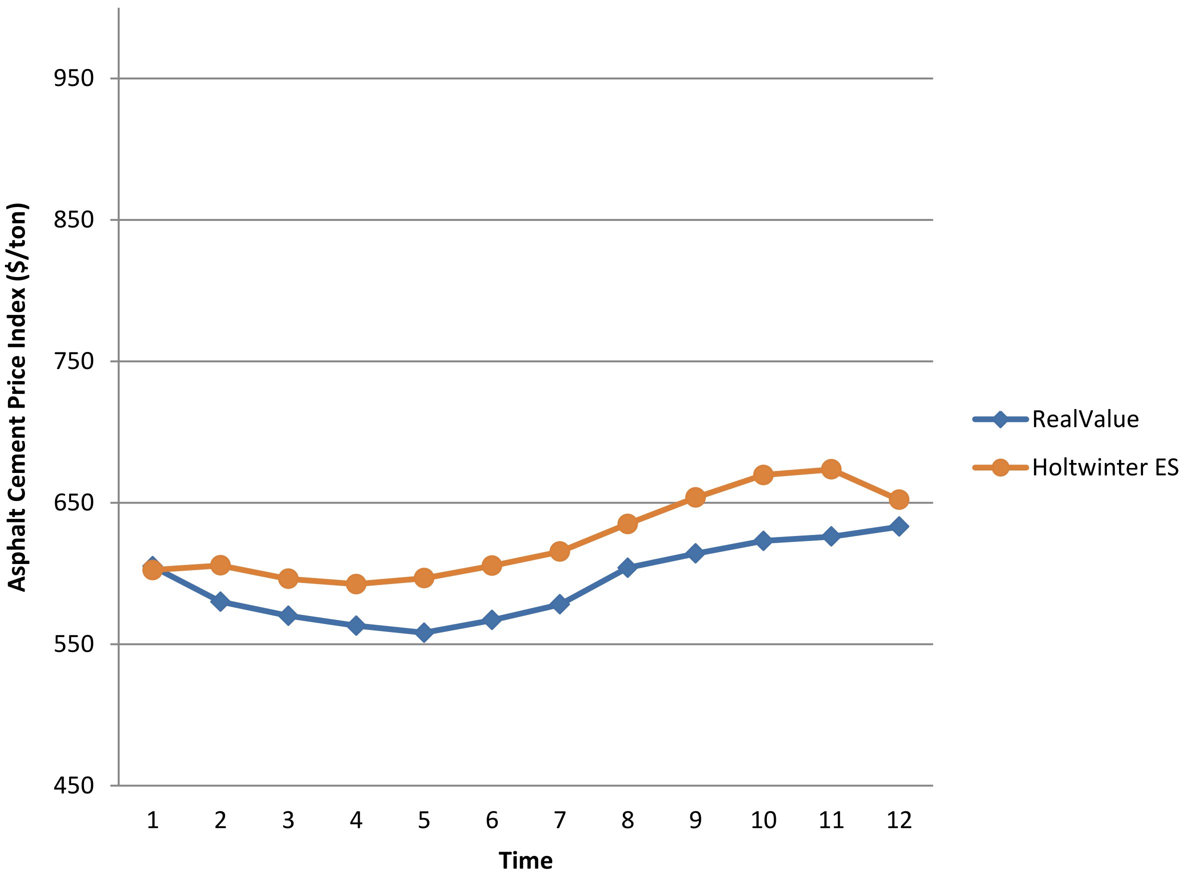
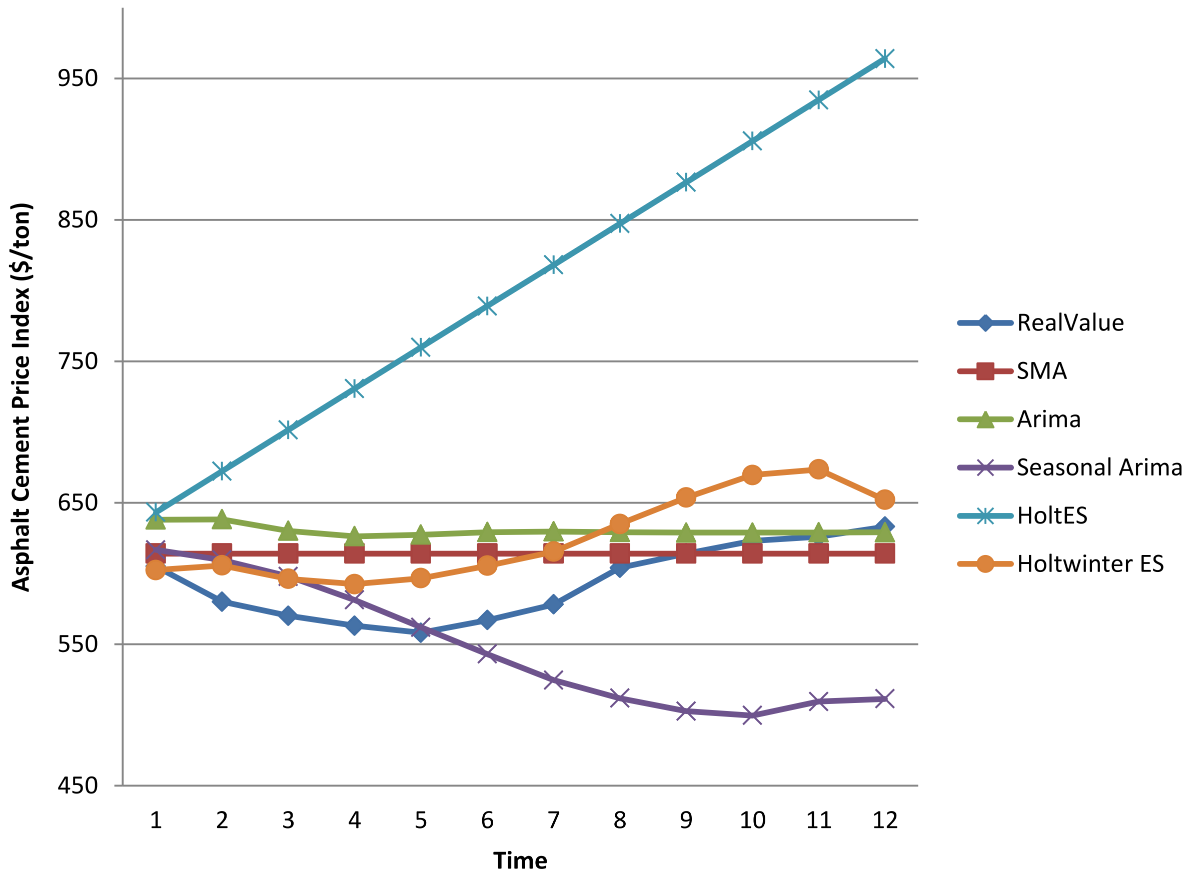


Results: Forecasted Values

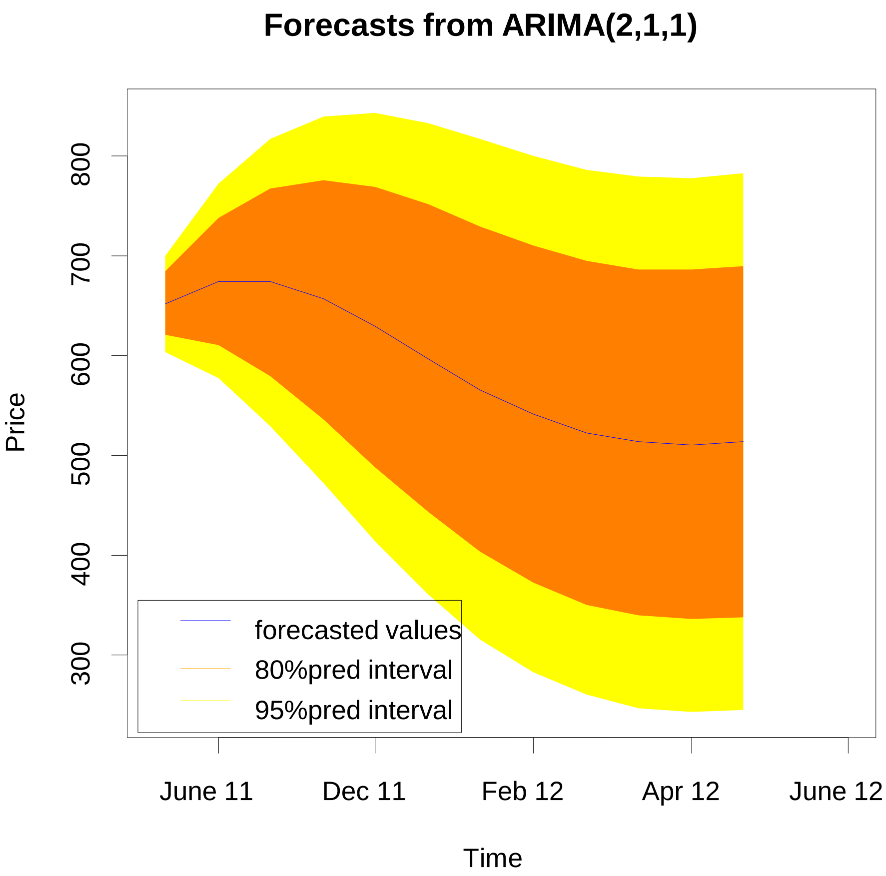


Results: Forecasted Values



Results: Forecasted Confidence Intervals

Confidence Intervals:



Conclusion

- Accurate forecasting of asphalt cement price index is possible by Time Series models

Accurate forecasting of material price can help:

- Contractors to submit more accurate and competitive bids
- State DOTs to consider more accurate budget
- Contractors and State DOTs to measure their risks and develop appropriate risk management strategies
- State DOTs to examine financial implications of offering Price Adjustment Clause (PAC) for asphalt cement

Limitations and Future Works

- **Limitations:**

  1- Not appropriate for long term forecasting

  2- Unable to perform well when a discrete jump occurs

- Measuring the value of Price Adjustment Clause (PAC)
- Develop procedure to determine risk contingencies
- Multivariate time series forecasting models

Acknowledgment

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Thank you for your attention!