Forecasting Pipeline Construction Costs Using Time Series Methods

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ABSTRACT

Pipe and labor costs constitute about seventy percent of pipeline project costs. The accurate prediction of pipe and labor costs is invaluable for cost estimation of capital pipeline projects by helping to eliminate or at least reduce cost under- or over-estimations. The research objective of this paper is to develop and compare various time series methods to forecast pipe and labor costs. The 20-city average pipe and labor costs from 1995 to 2016 published monthly by *Engineering News-Record (ENR)* were used to develop the time series models. The accuracies of these forecasting models were evaluated using ENR pipe and labor cost data from 2017 to 2019. The results show that predictions with seasonal autoregressive integrated moving average (ARIMA) models are more accurate than those with the other models, such as Holt exponential smoothing. The results contribute to pipeline construction community by helping cost estimators to prepare more accurate bids for pipeline projects.

INTRODUCTION

Many construction projects experience cost overruns. Most infrastructure construction projects face cost overruns (Flyvbjerg 2003). Cost overruns are generally caused by cost fluctuations (Memon et al. 2011). Large projects or megaprojects are more susceptible to cost fluctuations (Merrow 1988).

Pipeline construction projects, which are mostly long-term and large, are more likely to experience considerable fluctuations over time. Pipe material and labor costs constitute about 71% of pipeline construction costs (Rui 2011). These costs do not include equipment cost. Rui (2011) reported that the miscellaneous and right-of-way (ROW) costs constitute the other 29% of pipeline construction costs. On average, pipe cost has about 5%, and labor cost has 22% of overrun rates, which are large compared to the other cost overrun rates, such as miscellaneous cost (Rui 2012). Therefore, it is crucial to forecast fluctuations of pipe material and labor costs for pipeline construction projects.

Quantitative methods, especially time series models, have been used to forecast construction cost fluctuations (Ashuri et al. 2012a; Shahandashti 2014). Time series methods are proper methods for studying the variations of construction cost variables since they consider autocorrelation (Abediniangerabi et al. 2017). For example, Hwang et al. (2012) developed an Autoregressive Integrated Moving Average (ARIMA) model to forecast fluctuations of rebar, steel beam, and ready-mixed concrete costs. Shahandashti and Ashuri (2013) developed time series models to forecast ENR CCI. Also, fluctuations of ENR CCI were explained by economic, energy, and construction market variables (Ashuri et al. 2012b; Ashuri and Shahandashti 2012). Shahandashti and Ashuri (2016) explained fluctuations of national highway construction cost index using Vector Error Correction models. Ilbeigi et al. (2016) developed univariate time series models to forecast asphalt cement cost. They found that ARIMA and Holt Exponential Smoothing (Holt ES) models are more accurate than other univariate forecasting models. Time series methods have also been used to explain fluctuations in construction macroeconomic variables, such as construction spending (Abediniangerabi et al. 2018; Ahmadi and Shahandashti 2017). Despite the significant importance of fluctuations in pipeline construction costs, time series models have not developed to forecast these fluctuations.

The objectives of this research are to (1) investigate time series characteristics of pipe material and labor costs, (2) develop various univariate forecasting time series models for predicting pipeline construction costs, and (3) compare the forecasting accuracy between the univariate time series models for predicting pipeline construction costs.

Research methods are discussed in the next section. The research method section includes the description of four univariate time series models, including Holt exponential smoothing (Holt ES), Holt-Winters exponential smoothing (Holt-Winters ES), Autoregressive Integrated Moving Average (ARIMA), and seasonal ARIMA. Then empirical results, including descriptive statistics and validation of forecasting models for each time series, are provided. Conclusions are presented in the last section.

RESEARCH METHODS

Data Collection and Analysis

Engineering News-Record (ENR) publishes material and labor costs monthly. The material and labor cost indexes reported by ENR are the average costs of these items for major 20-cities in the United States. These indexes are publicly available. They do not represent all the costs and perspectives in the construction industry, but they reflect the contractor's perspective as an average input price index (Ashuri et al. 2012a). The ENR material and labor cost indexes could be used for adjusting construction cost for future changes.

As summarized in Table 1, ENR's reinforced concrete pipe cost, corrugated steel pipe cost, common labor cost, and skilled labor cost from January 1995 to August 2019 were used in this research. Four univariate time series models were developed using the data from January 1995 to December 2016. The forecasting accuracy of the models was evaluated based on error measures with the data from January 2017 to August 2019.

Table 1. Description of ENR Pipe Material and Labor Costs

Data	Description
Reinforced Concrete Pipe (RCP)	Average of 12″, 24″, 36″, 48″ monthly 20-city average cost
Corrugated Steel Pipe (CSP)	Average of 12″, 36″, 60″ monthly 20-city average cost
Common Labor (CL)	Two hundred hours of common labor at the 20-city average common-labor wage rates
Skilled Labor (SL)	68.38 hours of skilled labor at the 20-city average skilled labor wage rates

It is crucial to examine the characteristics of the time series before developing forecasting models. Stationarity and seasonality are two important properties of a time series (Shumway and Stoffer 2017). Stationarity indicates that statistical properties of time series, such as mean and covariance between two consecutive data points, are constant over time. Seasonality denotes repeating periodic cycles in time series (Brockwell and Davis 2002). The properties of a time series can be identified through decomposition. Decomposition divides a time series into three components, trend, seasonality, and random fluctuations (Kirchgässner and Wolters 2008).

Unit Root Test for Stationarity

Augmented Dickey-Fuller (ADF) test (Said and Dickey 1984) was conducted to examine the stationarity of each time series. The ADF test for reinforced concrete pipe cost is represented by Equation (1). The null hypothesis of the ADF test is non-stationarity of the given time series. The lag length used in the ADF test is determined by the Akaike Information Criterion.

$$\Delta RCP_t = \alpha + \beta t + \gamma RCP_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta RCP_{t-i} \quad (1)$$

where t is the time index, RCP_t is the reinforced concrete cost corresponding to time t, ΔRCP_t is the first differenced RCP_t, α is the drift term, β is the coefficient on a time trend, and γ is the coefficient to examine if it is required to differentiate the time series to be stationary.

Univariate Times Series Modeling

Univariate time series models including Autoregressive Integrated Moving Average (ARIMA), seasonal ARIMA, Holt Exponential Smoothing (Holt ES), and Holt-Winters Exponential Smoothing (Holt-Winters ES) were developed for each time series. Time series models were compared with one another based on the error measures: mean absolute percentage error (MAPE) represented by Equation (2), mean squared error (MSE) by Equation (3) and mean absolute error (MAE) by Equation (4).

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{\left|\hat{Y}_t - Y_t\right|}{Y_t} \times 100 \quad (2)$$

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(\hat{Y}_t - Y_t\right)^2 \quad (3)$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|\hat{Y}_t - Y_t\right| \quad (4)$$

where N is the total number of forecasted values, $\widehat{Y_t}$ is the forecasted cost by time series model at time t, and Y_t is the actual cost at time t.

ARIMA

ARIMA is recommended for nonstationary time series. ARIMA model consists of three parameters, p, d, and q. Parameter d is the minimum number of differencing to transform a nonstationary time series to a stationary time series. Parameter p and q are autoregressive (AR) order and moving average (MA) order, respectively. ARIMA (p, d, q) for reinforced concrete pipe cost is represented by Equation (5).

$$(1-B)^d RCP_t = \frac{\theta(B)}{\phi(B)} Z_t + \mu \quad (5)$$

where B is the backshift operator, d is the differencing order, μ is the mean of time series $(1-B)^d RCP_t$, $\phi(B)$ is AR operator, $\theta(B)$ is MA operator, and Z_t is the white noise component from a random variable with zero mean and finite variance.

Selecting AR and MA orders

AR and MA orders can be selected by autocorrelation function (ACF) and partial autocorrelation function (PACF) of a time series. Watson and Teelucksingh (2002) recommended the visual rules for selecting AR and MA orders based on ACF and PACF. If ACF values geometrically decay and PACF values cut off at lag *p,* it indicates AR order *p.* If ACF values cut off at lag *q* and PACF values geometrically decay*,* it indicates MA order *q*. If both the ACF and PACF geometrically decay, it indicates the ARMA process of a time series.

Estimation of AR and MA coefficients

The coefficients of AR and MA are estimated by maximum likelihood estimation (MLE). The coefficients with low p-value indicate that the developed ARIMA with the coefficients is appropriate for in-sample forecasting (Shumway and Stoffer 2017).

Seasonal ARIMA

Seasonal ARIMA is recommended for nonstationary and seasonal time series. Seasonal ARIMA applies the ARIMA method to nonseasonal components and seasonal components. A seasonal ARIMA model consists of six parameters, *p, d, q* for nonseasonal components and *P, D, Q* for seasonal components. Parameter *p* is the AR order for nonseasonal components, while *P* is the AR order for seasonal components. Parameter *d* is the minimum differencing order to make the nonseasonal components stationary while parameter *D* is the differencing order to make seasonal components stationary. Parameter *q* is the MA order for the nonseasonal components, while *Q* is the MA order for the seasonal components. Seasonal ARIMA $(p, d, q)(P, D, Q)_S$ for reinforced concrete pipe cost is represented by the following Equation (6).

$$(1-B)^d(1-B^S)^D RCP_t = \frac{\theta(B)\Theta(B)}{\phi(B)\Phi(B)} Z_t + \mu \tag{6}$$

where *B* is the backshift operator, *d* is the differencing order, *D* is the seasonal differencing order, *S* is the frequency of seasonality, μ is the mean of time series $(1-B)^d(1-B^S)^D RCP_t$, $\phi(B)$ is the AR operator for nonseasonal components, $\Phi(B)$ is the AR operator for seasonal components, $\theta(B)$ is the MA operator for nonseasonal components, $\Theta(B)$ is the MA operator for seasonal components, and Z_t is the white noise time series from a random variable with a zero mean and finite variance.

Selecting AR, MA orders of nonseasonal and seasonal components

The AR and MA orders for seasonal components in seasonal ARIMA are selected based on the observations of ACF and PACF. For seasonal components, lags at the multiple numbers of 12, which is the period of the seasonal cycle, should be carefully observed. The rules suggested by Watson and Teelucksingh (2002) can also be applied to select AR and MA orders of seasonal components. If PACF values of time series cut off at lag 12, the AR order of seasonal component is one. If ACF values of time series cut off at lag 12, its MA order of seasonal component is one.

Estimation of seasonal ARIMA coefficients

Seasonal ARIMA coefficients are estimated by maximum likelihood estimation. The coefficients with low p-value indicate that the developed ARIMA with the coefficients is appropriate for in-sample forecasting (Shumway and Stoffer 2017).

Holt ES

Holt ES is recommended for forecasting time series with a trend (Brockwell and Davis 2002). Holt ES for reinforced concrete pipe cost is represented by Equation (7). Holt ES consists of level and trend smoothing parameters. Smoothing parameters are recursively estimated by minimizing MSE of the in-sample forecasted values.

$$RCP_{t+h|t} = l_t + hb_t \tag{7}$$

where t is the time index, h is the forecasting period, l_t is the estimated reinforced concrete pipe cost level at time t, b_t is the estimated reinforced concrete pipe cost trend at time t, and $RCP_{t+h|t}$ is the h-step-ahead forecasted reinforced concrete pipe cost given the data until time t.

Holt-Winters ES

Holt-Winters ES is recommended for time series with trend and seasonality. Holt-Winters ES includes seasonal smoothing in addition to level and trend smoothing (Winters 1960). Holt-Winters ES is classified into additive ES and multiplicative ES. Holt-Winters additive ES assumes constant seasonality while Holt-Winters multiplicative ES assumes proportional seasonality. Holt-Winters additive ES and Holt-Winters multiplicative ES for reinforced concrete pipe cost are represented by Equation (8) and (9), respectively.

$$RCP_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)} \tag{8}$$

$$RCP_{t+h|t} = (l_t + hb_t)s_{t+h-m(k+1)} \tag{9}$$

where t is the time index, h is the forecasting period, m is the frequency of seasonality, k is the integer part of $(h-1)/m$, l_t is the estimated reinforced concrete pipe cost level at time t, b_t is the estimated reinforced concrete pipe cost trend at time t, s_t is the estimated reinforced concrete pipe cost seasonality at time t, and $RCP_{t+h|t}$ is the h-step-ahead forecasted reinforced concrete pipe cost given the data until time t.

Diagnostic Tests of Forecasting Model Residuals

Ljung-Box test (Ljung and Box 1978) was conducted to examine the lack of autocorrelation of the model residuals. The lack of autocorrelation among the residuals indicates the goodness of a fit of a forecasting model. The null hypothesis of the Ljung-Box test is that there is no autocorrelation in the residuals.

EMPIRICAL RESULTS

Trend and Seasonality

Table 2 shows the characteristics of pipe and labor cost time series, including trend and seasonality. Pipe and labor costs showed an increasing trend. Reinforced concrete pipe cost, corrugated steel pipe cost, and common labor cost revealed monthly seasonality while skilled labor cost did not show seasonality.

Table 2. Characteristics of Time Series

Data	Trend	Seasonality
Reinforced Concrete Pipe	Increasing	Monthly seasonal
Corrugated Steel Pipe	Increasing	Monthly seasonal
Common Labor	Increasing	Monthly seasonal
Skilled Labor	Increasing	No seasonality

Results of Unit Root Tests

According to the ADF test, pipe and labor cost time series are not stationary. Pipe and labor costs became stationary after applying one differencing order. Table 3 illustrates the ADF test results for the original and differenced time series.

Table 3. Results of ADF Unit Root Tests for Material and Labor Costs

Data	ADF *t-statistic*	Data	ADF *t-statistic*
RCP	-1.76 (6)	ΔRCP	-4.61[a] (6)
CSP	-2.83 (6)	ΔCSP	-4.77[a] (6)
CL	-3.02 (6)	ΔCL	-8.04[a] (6)
SL	-2.79 (6)	ΔSL	-7.92[a] (6)

Note: A delta (Δ) indicates the first difference operator; numbers in parentheses denote the lag orders which are selected based on the Akaike Information Criterion (AIC).
[a]Rejection of the null hypothesis at the 1% significance level.

Predictability of Time Series Models

ARIMA, seasonal ARIMA, Holt ES, and Holt-Winters ES models were implemented to material and labor cost time series. The forecasting accuracies between the models were compared with one another. Based on the time series from January 2017 to August 2019, MAPE, MSE, and MAE were calculated.

Reinforced Concrete Pipe (RCP)

Table 4 shows the results of the Ljung-Box test on the residuals of the forecasting models for reinforced concrete pipe cost. The results of the Ljung-Box test indicate that there is no autocorrelation between the residuals of the models except Holt-Winters Multiplicative ES.

Table 4. Diagnostic Tests of Model Residuals for Reinforced Concrete Pipe Cost

Ljung-Box Test	ARIMA	Seasonal ARIMA	Holt ES	Holt-Winters Additive ES	Holt-Winters Multiplicative ES
X-squared statistics	0.0486	0.2300	0.0013	0.1930	56.323[a]

[a]Rejection of the null hypothesis at the 1% significance level.

Table 5 shows that seasonal ARIMA has the lowest prediction errors. ARIMA model provides the second-best forecasts. Figure 1 compares the out-of-sample forecasting of each time series model and the actual ENR reinforced concrete pipe cost.

Table 5. Validation of Out-of-Sample Forecasting for Reinforced Concrete Pipe Cost

Measure	ARIMA	Seasonal ARIMA	Holt ES	Holt-Winters Additive ES	Holt-Winters Multiplicative ES
MAPE (%)	5.48	0.75	6.66	10.01	13.29
MSE	13.53	0.27	19.92	44.49	77.43
MAE	3.20	0.44	3.89	5.85	7.75

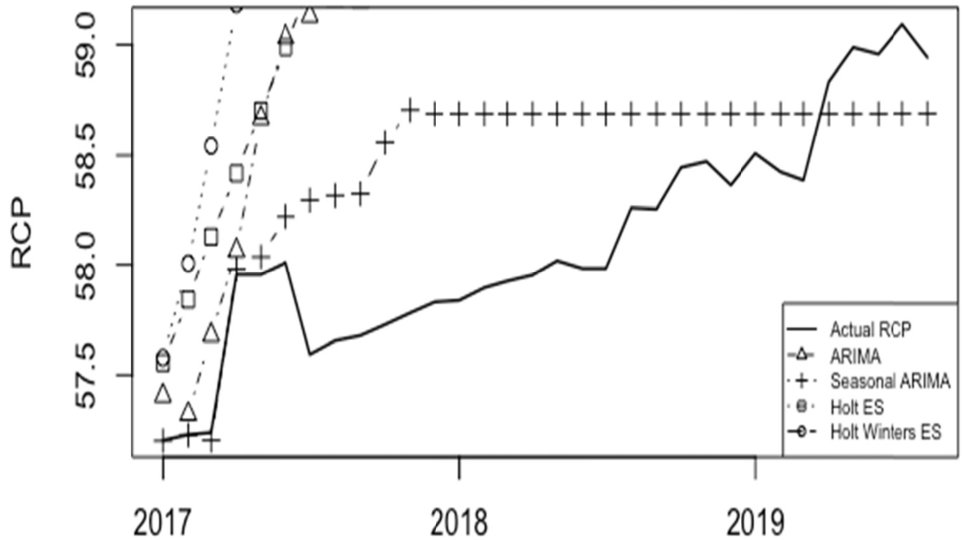

Figure 1. Out-of-sample forecasts of time series models and the actual Reinforced Concrete Pipe cost

Corrugated Steel Pipe (CSP)

Table 6 shows the results of the Ljung-Box test on the residuals of the forecasting models for corrugated steel pipe cost. The results of the Ljung-Box test indicate no autocorrelation between the residuals of the forecasting models except Holt-Winters Multiplicative ES.

Table 6. Diagnostic Test of Model Residuals for Corrugated Steel Pipe Cost

Ljung-Box Test	ARIMA	Seasonal ARIMA	Holt ES	Holt-Winters Additive ES	Holt-Winters Multiplicative ES
X-squared statistics	0.0222	0.0045	0.0689	0.4285	114.06[a]

[a]Rejection of the null hypothesis at the 1% significance level.

Table 7 shows that seasonal ARIMA provides the best forecasts for corrugated steel pipe cost time series. ARIMA has the second-best forecasting accuracy. Figure 2 compares the out-of-sample forecasting of each time series model and the actual ENR corrugated steel pipe cost. It shows the seasonal ARIMA is the most accurate forecasting model for the corrugated steel pipe cost.

Table 7. Validation of Out-of-Sample Forecasting for Corrugated Steel Pipe Cost

Measure	ARIMA	Seasonal ARIMA	Holt ES	Holt-Winters Additive ES	Holt-Winters Multiplicative ES
MAPE (%)	1.21	0.36	3.83	4.35	1.99
MSE	0.26	0.03	3.08	3.95	0.91
MAE	0.48	0.15	1.53	1.74	0.79

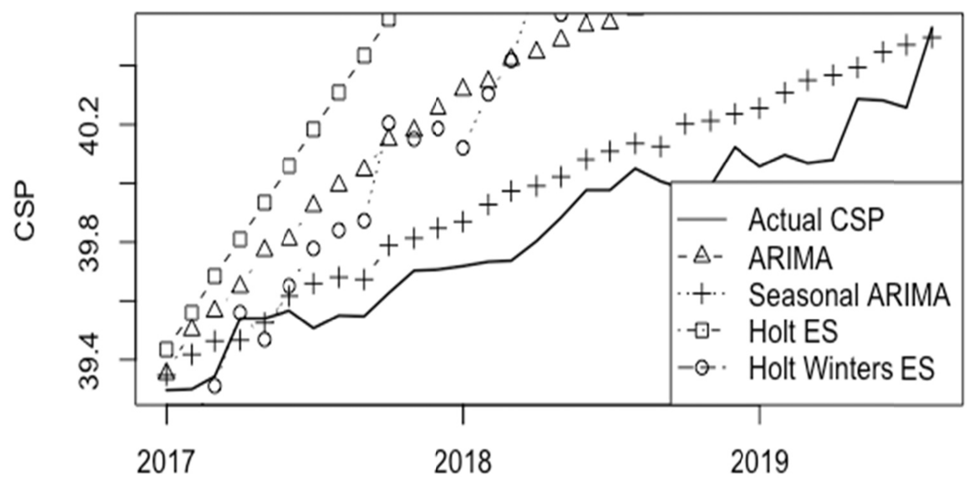

Figure 2. Out-of-sample forecasts of time series models and the actual Corrugated Steel Pipe cost

Common Labor (CL)

Table 8 shows the results of the Ljung-Box test on the residuals of time series models for the common labor cost. The results of the Ljung-Box test indicate that there is no autocorrelation between the residuals of the forecasting models except Holt-Winters Multiplicative ES.

Table 8. Diagnostic Test of Model Residuals for Common Labor Cost

Ljung-Box Test	ARIMA	Seasonal ARIMA	Holt ES	Holt-Winters Additive ES	Holt-Winters Multiplicative ES
X-squared statistics	0.0954	0.4856	0.0015	0.00009	92.55[a]

[a]Rejection of the null hypothesis at the 1% significance level.

Table 9 shows that Holt-Winters Additive ES is the best forecasting model. Figure 3 compares the out-of-sample forecasting of each time series model and the actual ENR common labor cost. It shows that all five univariate time series models accurately forecast the fluctuations of the common labor cost over two years.

Table 9. Validation of Out-of-Sample Forecasting for Common Labor Cost

Measure	ARIMA	Seasonal ARIMA	Holt ES	Holt-Winters Additive ES	Holt-Winters Multiplicative ES
MAPE (%)	0.3015	0.2978	0.2951	0.2715	0.5536
MSE	6634.77	7400.48	6231.77	5789.15	19771.14
MAE	69.66	69.01	68.10	62.77	120.86

Skilled Labor (SL)

Table 10 shows the results of the Ljung-Box test on the residuals of forecasting models for the skilled labor cost. The results of the Ljung-Box test indicate that there is no autocorrelation between the residuals of Holt ES and ARIMA.

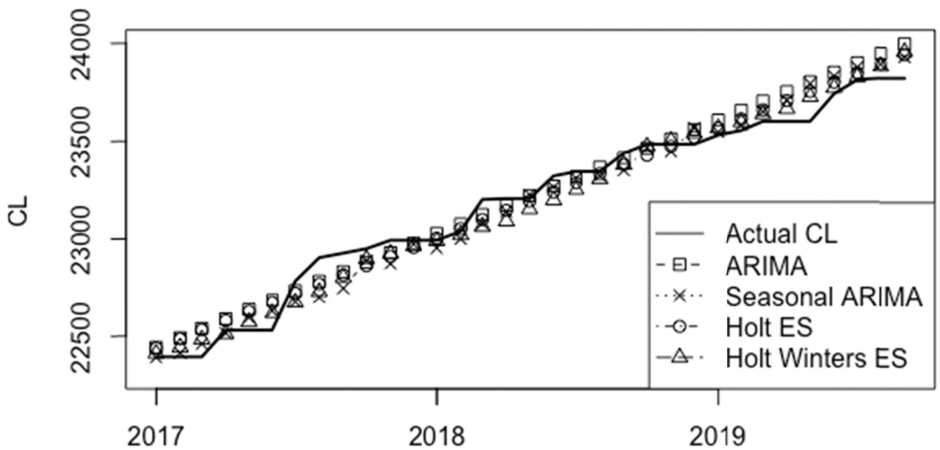

Figure 3. Out-of-sample forecasts of time series models and the actual Common Labor cost

Table 10. Diagnostic Test of Model Residuals for Skilled Labor Cost

Ljung-Box Test	**ARIMA**	**Holt ES**
X-squared statistics	0.5150	0.7863

Table 11 shows that ARIMA has better predictability than Holt ES. Figure 4 compares the out-of-sample forecasting of each time series model and the actual ENR skilled labor cost. Both time series models accurately forecast an upward trend of skilled labor cost.

Table 11. Validation of Out-of-Sample Forecasting for Skilled Labor Cost

Measure	**ARIMA**	**Holt ES**
MAPE (%)	0.9087	0.9572
MSE	10735.26	12045.71
MAE	93.85	98.89

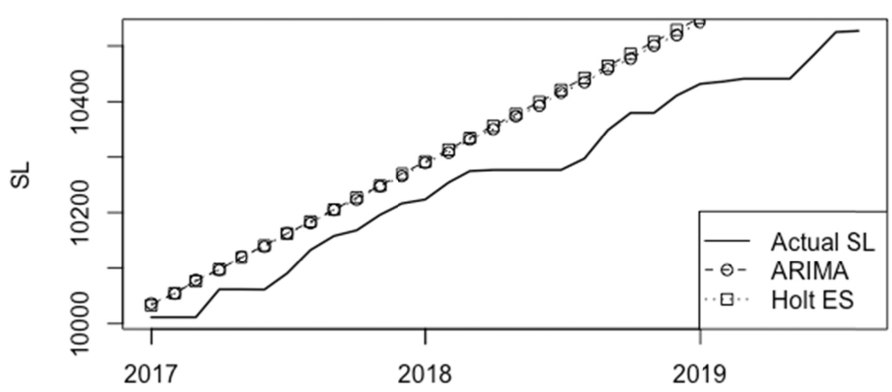

Figure 4. Out-of-sample forecasts of time series models and the actual Skilled Labor cost

CONCLUSION

Engineering News-Record (ENR) monthly publishes 20-city average costs of pipe material and construction labor in the United States. These cost indexes are subject to considerable fluctuations over time. Since these fluctuations can cause cost overruns in long-term pipeline projects, it is imperative to accurately forecast the cost fluctuations to avoid bid loss or profit loss. Forecasting material and labor cost as accurately as possible is certainly essential, considering that they consist of 71% of pipeline construction cost on average in the United States.

The accurate prediction of pipe and labor cost time series requires identifying its characteristics. The primary contribution of this research is identifying characteristics of pipe and labor cost time series and developing proper univariate time series models based on the characteristics of each time series to forecast its fluctuations.

The results of the ADF test showed that pipe material and labor cost time series are non-stationary. While material and common labor cost time series showed seasonality, skilled labor cost time series did not show seasonality. Based on the characteristics of each time series, univariate time series models were developed to forecast the cost fluctuations over two years, from January 2017 to August 2019. ARIMA, seasonal ARIMA, Holt ES, and Holt-Winters Additive ES passed the diagnostic tests indicating the goodness of a fit. The empirical results presented the forecasting accuracy of developed univariate time series models. Among these models, seasonal ARIMA generally showed the best predictability for seasonal time series and ARIMA showed the best predictability for nonseasonal time series. For pipe costs, seasonal ARIMA provided the best forecasting accuracy with the least MAPE, MSE, and MAE. For the common labor cost, Holt-Winters ES had better forecasts than seasonal ARIMA. For the skilled labor cost, ARIMA predicted better than Holt ES.

The findings of this paper contribute to the body of knowledge by understanding the time series characteristics of pipe and labor costs and forecasting the fluctuations of pipe and labor costs using time series models. These time series methods can also be used for adjustments of future changes in other construction cost indexes. It is expected that these results help cost estimators and capital project planners to adjust future cost changes in long-term and large pipeline projects.

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