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RESEARCH ARTICLE

Time series analysis of building construction cost index in Türkiye

Serkan Aydınlı

Cukurova University, Department of Civil Engineering, Adana, Turkiye

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Abstract

Successful cost prediction is one of the major issues in the construction industry. Practitioners and researchers use many methodologies to determine accurate project budgets. Time-series analysis is a widely used projection determination tool, that allows accurate forecasting in many areas such as financial analysis, temperature forecast, etc. This paper aims to determine the efficiency of time-series analysis in forecasting construction costs in Türkiye. To that end, construction cost index (CCI) data between 2015-2022 were used and two main time-series analysis methods; Holt-Winters Exponential Smoothing (Holt-Winters ES) and Autoregressive Integrated Moving Average (ARIMA) have been employed. The results showed that all models underperformed in an environment with high inflation. However, considering all models, the triple exponential smoothing model showed the relatively best forecasting performance. It is suggested that the prediction performance can be improved using multivariate models and machine learning techniques.

1. Introduction

The construction industry is one of the leading sectors for developing economies. Total investment in construction in 2020 is 78 billion € in Türkiye and the industry accounts for 5.4% of the total GDP [1]. Industry stakeholders make important contributions and lead many economic activities. In a sector with such large investments, cost analysis is also of great importance for construction companies.

The cost performance of construction projects is the most crucial factor according to many project managers. Many factors that affect the cost performance of construction projects should be considered by practitioners. Cost increases can both reduce the success of the project and cause conflicts between the parties [2]. Literature studies showed that inflation [3,4] and exchange rate fluctuations [5] affect cost performance significantly. The inflation rate, in other words, the consumer price index, means the movements of general price fluctuations. The inflation rate drives many price factors such as material and labor prices in construction projects. Exchange rates, another major cost fluctuations factor is regarding purchasing power of the local currency. The exchange rate also drives the cost of imported goods such as energy, material, equipment, etc. Therefore, predicting the direction of future construction costs has great importance, especially in countries with high inflation rates and fluctuating exchange rates. The industry is also affected by political and social factors. This situation makes it more difficult to detect the changes in construction

Correspondence Serkan Aydınlı saydinli@cu.edu.tr

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costs. In such an environment, robust and effective tools/models should be used for cost estimation.

Economics and finance literature employs many models for forecasting. Time series analysis is used in many branches of science such as financial analysis [6], planning and management [7], engineering [8], and nature [9]. As can be seen, time series analysis has been successfully used in various fields for future forecasting and projection. It is considered that adapting the univariate time series models, which are widely used in many fields, to cost prediction studies will be a significant development for construction management literature [10].

Nowadays, changes in construction costs over time are observed using CCI. Studies on CCI estimation have gained momentum over time and practitioners are increasingly using CCI data when project budgeting. However, contrary to the general trend, studies on CCI prediction are still underworked in Türkiye. In this context, investigating CCI in Türkiye, which is a major example for developing countries, will provide significant contributions to the literature.

In this study, the prediction power of time series analysis on construction costs has been investigated. For this purpose, univariate time series models that are Holt-Winters ES and ARIMA, have been employed and their efficiencies on CCI forecasting in Türkiye are determined. Thus, it is aimed to lead important developments in construction cost forecasting literature, especially in developing economies.

2. Related works

The effect of inflation on costs in the construction industry has forced researchers to conduct studies on the estimation of future costs. Many CCI prediction studies have been carried out in construction management literature over the last decades.

One of the first efforts at CCI forecasting studies has been conducted by Wang and Mei [11]. The authors explained the calculation process of CCI and they proposed an analytic model for CCI forecasting. As a result, they showed that the predicted and observed values are very close and errors are within the 95% confidence interval. Ashuri and Lu [10] predicted Engineering News Records (ENR) CCI using Holt ES and ARIMA methods which are also employed in this study. The study showed that while ARIMA model produces more accurate predictions for in-sample data, Holt ES is more accurate for out-of-sample data. The widespread use of ARIMA models continued in the forecasting of material prices. Hwang et al., [12] forecasted material unit prices using ARIMA models and automated model parameter selection procedures. The results showed that the proposed automated model can determine model parameters successfully and models can predict material unit prices within acceptable error limits. Another study on material price forecasting was conducted by Ilbeigi et al., [13]. Authors forecasted the asphalt cement price index for Georgia in the USA using time series models such as Holt ES, Holt-Winters ES, and ARIMA. The result of the study showed that in parallel with Ashuri and Lu [10], the Holt ES model gave better forecasting performance. Moon and Shin [14] employed an interrupted ARIMA model for ENR CCI prediction. The authors tested the effects of interruptions such as the 2008 global crisis. The authors concluded that interrupted time series models are more effective in case of interruptions in time series data. Moon et al. [15] employed ARFIMA model which is a fractionally integrated ARIMA model. The authors argue that the fractional integration process can enhance ARIMA model performance and the experimental study validated them. The error rate of ARFIMA model is significantly lower than ARIMA error. Wang et al., [16] studied China's case and they forecasted building material prices using ES models and grey prediction models. The authors concluded that the grey model and polynomial fitting methods are two effective prediction models for material price prediction in China. Zhao et al. [17] forecasted the New Zealand building construction cost index using Holt ES and ARIMA methods. As a result of the study, no significant superiority was found between the models.

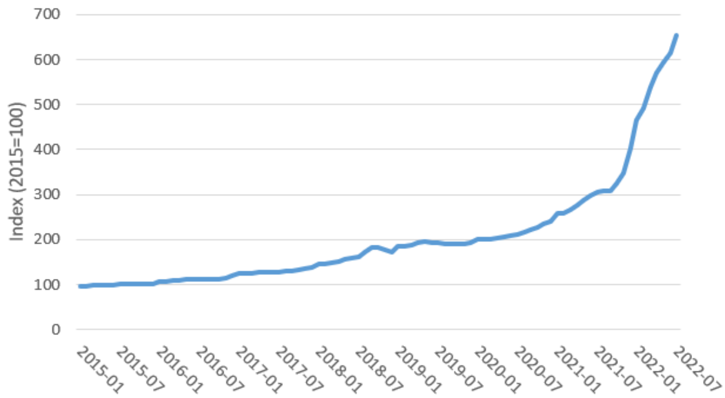
Compared to the literature on developed countries, there are few studies conducted using Türkiye CCI data. Kibar [18] forecasted the building cost index (BCI) using time series models which is one of the preliminary studies. The author collected quarterly BCI data from 1991 to 2005 and employed Holt ES, ARIMA, and SMA techniques as univariate time series models. The author concluded that the forecasting performance of ARIMA model is slightly better than Holt ES. On the other hand, Genç [19] employed a regression model to predict the building material cost index in Türkiye and used the exchange rate of the US Dollar as an independent variable. The author concluded that the exchange rate is significant for the prediction of the building material cost index. Some researchers have also examined the relationship between macroeconomics and the construction cost index. Fındık and Öztürk [20] investigated the impact of macroeconomics using symmetric causality analysis. Data from 2005 to 2015 were obtained from the Central Bank of Türkiye and TURKSTAT. Authors have pointed out that there are long-term causal effects of the exchange rate of the US Dollar on CCI. In another study, Aydınlı [21] used Autoregressive Distributed Lag (ARDL) cointegration model and Granger Causality Test to identify causal relationships between macroeconomics and CCI in Türkiye. The author concluded that there are significant relationships between the producer price index (PPI), the exchange rate of the US Dollar, and CCI.

Considering literature studies, it is clearly shown that there is no case study conducted on developing economies with a high inflation rate. Thus, this study aims to test conventional univariate time series models respectively; Holt-Winters ES and ARIMA on Türkiye CCI data.

3. Methodology

3.1. Data collection

The CCI is an index composed of construction material, equipment, and labor costs. The index data is monthly published by the Turkish Statistical Institute (TURKSTAT). CCI has been published since the 1980s, and recently, the 2015=100 index, which was improved by changing the calculation method and inputs, continues to be published today. TURKSTAT has developed the monthly index by analyzing 77 construction projects and calculating by tracking the prices of 2300 items. Data from January 2015 to July 2022, which are the updated series, were used within the scope of the study. Changes in the index between 2015-01 and 2022-07 are as given in Fig. 1. The figure shows that CCI has been in an uptrend and this rise seems to have become quite aggressive, especially as of 2021. During the evaluation of the models, the dataset was divided into two groups as the training-test data set. While training data cover 2015-01 – 2020-08 (70%), test data cover 2020-9 – 2022-07 (30%).



Source: TURKSTAT

Fig. 1. CCI Data (2015-2022

3.2. Holt-Winters ES

Holt-Winters ES which was first introduced by Holt [22] and Winters [23] is a widely used univariate time-series forecasting model [24]. Holt [22] and Winters [23] first used this method in marketing for short-term sales projections [17]. Holt-Winters helps to model three characteristics of time series respectively; level (a), trend (b), and seasonality (c). Similar to other univariate models, Holt-Winters uses past values to predict future values. The method also weights the past values using the exponential smoothing technique which smooths the time series. This study employs three approaches; Single Exponential Smoothing (SES) as a base method, Double Exponential Smoothing (DES) (aka Holt's Method), and Triple Exponential Smoothing (TES) (aka Holt-Winters Method). The equations of these approaches are given below respectively;

$$y_t = \alpha x_t + (1-\alpha) y_{t-1} \tag{1}$$

$$y_t = \alpha x_t + (1-\alpha)(y_{t-1} + b_{t-1}) \tag{2}$$

$$y_t = \alpha \frac{x_t}{c_{t-L_t}} + (1-\alpha)(y_{t-1} + b_{t-1}) \tag{3}$$

where;

y_t: smoothed statistic (weighted average of current observation x_t

x_t: current observation

α: smoothing factor; $0 < \alpha < 1$

t: time period

b_t: best estimate of a trend at time t

c_t: sequence of seasonal correction factor at time t

As understood from equations, SES uses only a smoothing level factor that provides stable predictions. Thus, this method is recommended for time series with no trend and no seasonality. DES uses the trend factor as well as the level. The last approach, TES uses both trend and seasonality factors as well as the level factor. As can be seen, each method produces estimates by taking into account different features. Therefore, the prediction accuracy of the methods is directly affected by the features of the data, and the superiority between them is shaped by the data characteristics.

3.3. ARIMA implementation

ARIMA models, in other words, Box-Jenkins models, were first developed and introduced by Box and Jenkins [25] to model univariate time series and make successful predictions. The modeling strategy of this approach is based on autoregressive (AR) and moving average (MA) components. ARIMA models are implemented in two ways, non-seasonal and seasonal. Equations of AR and MA components are given below;

Order of non-seasonal ARIMA: ARIMA (p,d,q)

Order of seasonal ARIMA: SARIMA (P,D,Q)(p,d,q)

$$\emptyset_p(B)\nabla^d y_t = c + \theta_q(B)\varepsilon_t \tag{4}$$

$$\emptyset_p(B)\Phi_P(B)^S\nabla_S^D\nabla^d y_t = c + \theta_q(B)\Theta_Q(B^S)\varepsilon_t \tag{5}$$

where:

y_t: predicted y value at t. time.

c: regression constant

S: Seasonal order (e.g. S=12 for monthly data)

$B = B^m y_t = y_{t-m}$ (backshift operator)

$\emptyset_p(B) = 1 - \emptyset_1 B^1 - \cdots - \emptyset_p B^p$ (p. degree autoregressive component)

$\Phi_P(B) = 1 - \Phi_1 B^S - \cdots - \Phi_P B^{PS}$ (P. degree seasonal autoregressive component)

$\nabla^d: (1 - B^1)^d$ (differencing component)

$\nabla_S^D: (1 - B^S)^D$ (seasonal differencing component)

$\theta_q(B) = 1 + \theta_1 B^1 + \cdots + \theta_q B^q$ (q. degree moving average component)

$\Theta_Q(B) = 1 + \Theta_1 B^S + \cdots + \Theta_Q B^{QS}$ (Q. degree seasonal moving average component)

The main steps of the ARIMA model implementation are performed in the following order:

1) Stationary test of time series
2) Order selection and parameter estimation
3) Checking model diagnostics
4) Forecasting and model evaluation

One of the assumptions of ARIMA implementation is that the time series data should be stationary. Thus, the first step is the stationary test using Augmented Dickey-Fuller (ADF) Test [26]. ADF test is a hypothesis test in which the null hypothesis is "Time series has a unit root and is non-stationary". In case the time series is not stationary, the difference of the series should be taken and tested again. This process is repeated until the time series is stationary. At the same time, the I operator of the ARIMA model, as the difference operator, expresses at which difference level it becomes stationary. The order selection and parameter estimation refer to model tuning to fit the data. At this stage, p, d, q parameters, and regression coefficients are determined. Checking model diagnostics is of a significant role to determine the usability of the model for forecasting. Model diagnostics covers Ljung-Box (LB) Test that examines whether model residuals follow white noise [27].

3.4. Train – Test split and evaluation of models

As mentioned before, monthly data employed for analysis cover January 2015 – July 2022. The train – test split procedure has been applied considering a 75% - 25% ratio. In this way, 68 time-series data points from January 2015 to August 2020 were determined as training data and 23 time-series data points from September 2020 to July 2022 were determined as test data. Thus, a minimum of 50 data points required for the training of time series models (Box and Tiao [28]) were provided.

The last stage of implementation is model evaluation. Two error measures; root mean square error (RMSE) (Eq. 6) and root mean squared percentage error (RMSPE) (Eq. 7) determine models' performances.

$$\sqrt{\sum_{1}^{n} \frac{(\mathrm{Predicted_i} - \mathrm{Actual_i})^2}{\mathrm{n}}} \tag{6}$$

$$\sqrt{\frac{\sum_1^n \left(\frac{(Predicted_i - Actual_i)}{Actual_i}\right)^2}{n}} \tag{7}$$

All analyses in this paper were conducted using Python 3.8 environment. The functions for Holt-Winters and ARIMA implementation; holt-winters, ARIMA, and SARIMA functions are imported from statsmodels. ADF tests were conducted using adfuller function. auto_arima function determined the model parameters and model diagnostics were determined using acorr_ljungbox function.

4. Results and discussion

4.1. Decomposition of CCI data

The determination of the features of the time series plays an important role in discussing the models' performances. CCI data were first decomposed into trend, seasonal and residual components (Fig 2).

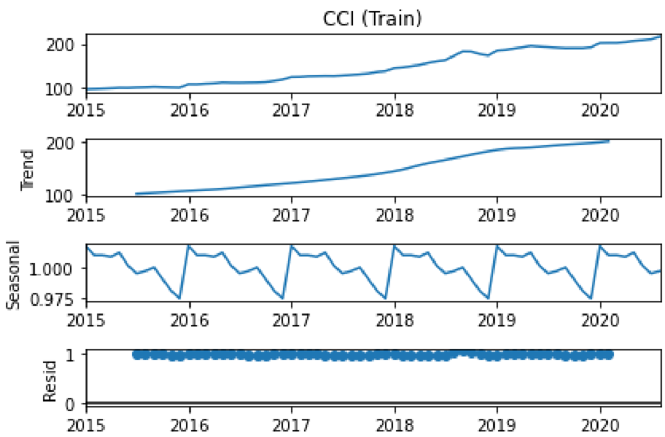


Fig. 2. Decomposition of CCI data

While the trend component implies long-term tendency, the seasonality component means the effects of seasonal features on time series. On the other hand, residuals represent changes that cannot be explained by trend and seasonality components. Fig 2 indicates that CCI in Türkiye is on an upward trend and is of low seasonality. Index data also show high residuals, which mean high volatility and differ from other developed economies. This paper discusses the efficiency of time series analysis methods on such data.

4.2. Models' forecasting performances

In this study, CCI data in Türkiye were forecasted using Holt-Winters ES and ARIMA which are two widely used time series analysis methods. The first step of the forecasting process is to determine the appropriate model parameters. In this phase, while the Holt-Winters ES method does not have any assumptions, the ARIMA method acts on the assumption that the time series is stationary. Therefore, the stationarity test should be applied to the time series, and if the series is not stationary, it should be made stationary using the difference method. As mentioned before, Augmented Dickey-Fuller (ADF) Test is employed to determine whether the data is stationary or not. ADF test results are presented in Table 1.

Hypothesis test results show that while original data is non-stationary, the first differenced series are stationary. From this, it is understood that the ARIMA model should take the first-order difference of the series.

The second step is the order selection and parameter estimation of models. Information criterion is a major goodness of fit criterion during the determination of the model coefficients. Commonly used information criteria in the literature are Akaike Information Criterion (AIC) [29], Bayesian Information Criterion (BIC) [30], and Hannan-Quinn Information Criterion (HQIC) [31]. Researchers usually determine model parameters according to these information criteria. The basic condition is to determine the parameters that minimize the information criterion. In this study, AIC and BIC were employed as goodness of fit criteria. Model parameters are given in Table 2.

Table 1. ADF test results

	CCI (Türkiye)				
	ADF Test Statistics	Critical Value (10%)	Critical Value (5%)	Critical Value (1%)	p-value
Original data	0.804232	-2.591103	-2.907154	-3.535217	0.991704
1st differenced data	-5.913846	-2.591103	-2.907154	-3.535217	0.000002

Table 2. Holt-Winters ES and ARIMA model parameters

Holt-Winters ES					
Model Name	Level Coefficient	Trend Coefficient	Seasonality Coefficient	AIC	BIC
SES	0.154	-	-	343.753	348.192
DES	1.000	0.000	-	155.934	164.812
TES	1.000	0.202	1.465×10^{-8}	138.329	173.841
ARIMA					
Model Name	Order	AR Coefficients	MA Coefficients	AIC	BIC
SARIMA	$(2,1,0)(1,0,2)_{(12)}$	L1 0.588 L2 -0.309 S L1 0.998	S L1 -1,075 S L2 -0.176	316.740	332.067

Table 2 presents all model parameters and coefficients. According to AIC, the best-fit model is TES which takes into account both trend and seasonality, while BIC points to DES as the best-fitted model. On the other hand, Seasonal ARIMA (SARIMA) does not fit as well as TES and DES. Model diagnosis is the last step of ARIMA implementation. For this purpose, Ljung-Box test was conducted and p-value was determined as 0.976 which means that there is no autocorrelation and the model is convenient for forecasting. Although model parameters gave important findings regarding forecasting performances, measuring the performance of models on test data is also a major determinant. Models' performances are given in Table 3 and Fig. 3.

Models' performance evaluations showed parallel results with the goodness of fit criteria. The best forecasting model is TES, which accounts for both trend and seasonality components. This result also confirms the literature studies of Ashuri and Lu [10] and Zhao et al. [17]. It is crucial to discuss models' forecasting performance on CCI prediction since practitioners should be properly informed regarding the effectiveness of the methods. The TES model with the best forecasting performance takes trend and seasonality into account. On the other hand, other models underperformed due to their structure. SES and DES models are simpler models than TES. The SES model considers the only level of time series data and makes very linear predictions. DES model considers both level and trend components and makes more accurate predictions, particularly with time series with the trend. Even though SARIMA also takes seasonality into account, it mostly depends on regression of its own lagged values which causes mostly linear predictions and also affected train – test split point. On the other hand, it is observed that models have extremely low performance in forecasting test data. Test data cover the 2020-9 – 2022-07 period which is highly volatile. The volatility of the exchange rate ($/TL), raising consumer price index (CPI), and producer price index (PPI) affect directly CCI and its general trend.

Table 3. Models' Forecasting Performance Evaluations

	SES	DES	TES	ARIMA
RMSE	215.576	182.286	170.153	182.162
RMSPE	4.271	3.448	3.177	3.443

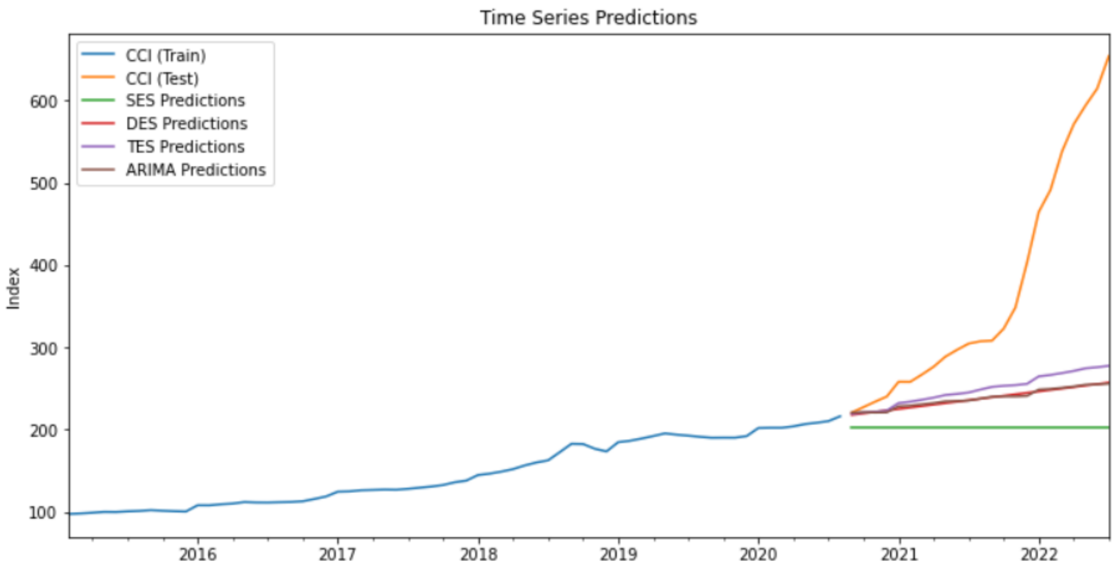


Fig. 3. Models' Predictions

Today, the construction industry is among the sectors where both imports and exports are intense. Many building material groups such as cement and steel constitute an important item in exports. On the other hand, building materials used especially in fine works are also imported. In addition, the construction industry is one of the most energy-intensive industries. Therefore, volatility in exchange rates and changes in oil prices directly affect sector costs. Considering the 2021-2022 period, it is seen that these two factors come together and it caused a significant rise. It is understood that univariate time series models are quite inadequate in such scenarios. Such models are successful only in low inflation and more predictable economic environments. In turbulent and uncertain economies, such models make predictions with high error rates.

Many studies use Building Information Modeling (BIM) which is another widely used tool for cost estimation. These studies mostly focused on cost prediction using design details & changes [32, 33]. It is also possible that these time-series models can be adapted to BIM-based prediction. These techniques may help to improve prediction accuracy, especially in static economic conditions. On the other hand, these techniques may be insufficient in fluctuating environment.

It is thought that it would be more beneficial to apply multivariate time series models to improve forecast performance in volatile economies. Multivariate models were also applied in economies with low inflation and it was observed that better results were obtained than univariate models [34]. Multivariate models take into account the trend and seasonality of the time series as well as the effects of exogenous variables on the time series. Thus, the effects of many parameters such as exchange rate and producer price index that directly affect the construction costs will be reflected in the models.

5. Conclusion

Future cost prediction is one of the crucial issues, especially in Türkiye. Project performances decrease and construction companies cannot reach target profitability mostly due to unrealistic cost estimates. Thus, the importance of cost forecasting is increasing. Today, time series models are frequently used in future predictions. However, there are few studies conducted using time series analysis methods in the field of construction management. This study aimed to forecast CCI in Türkiye using univariate time series analysis methods. In this context, widely used time series analysis methods; Holt-Winters ES and ARIMA were employed and monthly CCI time series data published by TURKSTAT were collected. Analyses showed that the TES model makes more accurate predictions than other models. On the other hand, especially in volatile economic environments, it is observed that models' accuracies are low. It is thought that it would be more appropriate to apply multivariate time series models to better predict the cost index, which is directly affected by exchange rates. In addition, prediction models can be strengthened with machine learning techniques and useful algorithms for practitioners can be developed. As a result, future forecasts are of great importance for project success, especially in volatile economies such as Türkiye. Univariate and multivariate time series analyses are among the major econometric techniques for future predictions. Considering univariate models, it is seen that TES models produce the most appropriate results for the Türkiye case. As a result, it is thought that univariate time series models are of the potential to help contractors and investors in cost prediction. Predictions on construction costs throughout the construction process can be made using these methods. However, the paper shows that such techniques may not perform well, especially during periods of volatility and high inflation. In such periods, the use of multivariate models may provide better predictions.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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References

[1] FIEC. FIEC 2021 Statistical Report Turkey
[2] Bayram S (2018) Revised unit price practice in Turkish construction works. J Constr Eng Manag Innov 1(4): 162–70.
[3] Okpala DC, Aniekwu AN (1988) Causes of High Costs of Construction in Nigeria. J Constr Eng Manag 114(2): 233–44.
[4] Kaming PF, Olomolaiye PO, Holt GD, Harris FC (1997) Factors influencing construction time and cost overruns on high-rise projects in Indonesia. Constr Manag Econ 15(1):83–94.
[5] Enshassi A, Mohamed S, Abushaban S (2009) Factors affecting the performance of construction projects in the Gaza Strip. J Civ Eng Manag 15(3): 269–80.
[6] Crespo Cuaresma J, Hlouskova J, Kossmeier S, Obersteiner M (2004) Forecasting electricity spot-prices using linear univariate time-series models. Appl Energy 77(1): 87–106.
[7] Wong JMW, Chan APC, Chiang YH (2011) Construction manpower demand forecasting. Eng Constr Archit Manag 18(1):7–29.
[8] Kalman RE (1960) A new approach to linear filtering and prediction problems. J Basic Eng 82(1): 35–45.
[9] Koçak K, Şaylan L, Eitzinger J (2004) Nonlinear prediction of near-surface temperature via univariate and multivariate time series embedding. Ecol Modell 173(1):1–7.
[10] Ashuri B, Lu J (2010) Time series analysis of ENR construction cost index. J Constr Eng Manag 136(11):1227–37.
[11] Wang C-H, Mei Y-H (1998) Model for forecasting construction cost indices in Taiwan. Constr Manag Econ 16(2):147–57.
[12] Hwang S, Park M, Lee HS, Kim H (2012) Automated time-series cost forecasting system for construction materials. J Constr Eng Manag 138(11):1259–69.
[13] Ilbeigi M, Ashuri B, Joukar A (2017) Time-series analysis for forecasting asphalt-cement price. J Manag Eng 33(1): 1–9.
[14] Moon T, Shin DH (2018) Forecasting construction cost index using interrupted time-series. KSCE J Civ Eng 22(5):1626–33.
[15] Moon S, Chi S, Kim DY (2018) Predicting construction cost index using the autoregressive fractionally integrated moving average model. J Manag Eng 34(2): 04017063.
[16] Wang QK, Mei TT, Guo Z, Kong LW. Building material price forecasting based on multi-method in China. IEEE Int Conf Ind Eng Eng Manag. December 2019.
[17] Zhao L, Mbachu J, Zhang H (2019) Forecasting residential building costs in New Zealand using a univariate approach. Int J Eng Bus Manag 11: 1-13.
[18] Kibar MA. Building cost index forecasting with time series analysis. MSc Thesis, Middle East Technical University, 2007.
[19] Genç O. Döviz Kuru Kullanılarak Bina İnşaat Malzemeleri Maliyet Endeksinin Tahmin Edilmesi. In: 1st International Conference on Innovative Academic Studies. 2022 p. 490–3 Konya, Türkiye.
[20] Fındık H, Öztürk E (2016) The examination of the impact of macroeconomic indicators on the construction sector costs by the guidance of symmetric causality analysis. Eurasian Bus Econ J 2: 319–29.
[21] Aydınlı S. Causal Relationships between Construction Cost Index and Macroeconomics in Turkey. In: 7th International Project and Construction Management Conference (IPCMC2022). 20-22 October 2022, p. 525–33 İstanbul, Türkiye.
[22] Holt CE (1957) Forecasting trends and seasonal by exponentially weighted averages. ONR Memo 52: 5–10.
[23] Winters PR Forecasting sales by exponentially weighted moving averages. Manage Sci 6(3): 324–42.
[24] Hyndman RJ, Koehler AB, Snyder RD, Grose S (2002) A state space framework for automatic forecasting using exponential smoothing methods. Int J Forecast 18(3): 439–54.
[25] Box GEP, Jenkins GM Time Series Analysis: Forecasting and Control. San Francisco: Holden-Day, 1975.
[26] Dickey DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 74(366a): 427–31.
[27] Ljung GM, Box GEP (1978) On a measure of lack of fit in time series models. Biometrika 65(2): 297–303.

[28] Box GEP, Tiao GC (1975) Intervention analysis with applications to economic and environmental problems. J Am Stat Assoc 70(349): 70–79.

[29] Akaike H (1974) A new look at the statistical model identification. IEEE Trans Automat Contr 19(6): 716–23.

[30] Schwarz G (1978) Estimating the dimension of a model. Ann Stat 6(2): 461–464.

[31] Hannan EJ, Quinn BG (1979) The determination of the order of an autoregression. J R Stat Soc Ser B 41(2): 190–5.

[32] Lawrence M, Pottinger R, Staub-French S, Nepal MP (2014) Creating flexible mappings between Building Information Models and cost information. Autom Constr 45: 107–18.

[33] Wang K-C, Wang W-C, Wang H-H, Hsu P-Y, Wu W-H, Kung C-J (2016) Applying building information modeling to integrate schedule and cost for establishing construction progress curves. Autom Constr 72: 397–410.

[34] Hwang S (2011) Time series models for forecasting construction costs using time series indexes. J Constr Eng Manag 137(9): 656–62.