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Consolidation of Time Series Models for the Prediction of XUTEK Index and Technology Stocks in Istanbul Stock Exchange during Pandemic Period

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Abstract

Due to the closure experienced during the pandemic, many investors divert their investments to different exchanges. In this sense, it has been observed that while sectors such as transportation, banking, and services have seriously lost value, especially the technology sector has come forward and gained value. In this research, we move the study one step forward by proposing a consolidated forecast system instead of employing a model to estimate the price of the Istanbul Stock Exchange Technology Index (XUTEK) which consists of 19 technology companies traded in BIST, and technology stocks. Stock movements during the pandemic period between 01.01.2020 and 01.09.2020, when technology stocks gained considerable value, are investigated to estimate the price of XUTEK. For each technology stock and XUTEK index, five different time series models are modeled namely, Holt's linear trend, simple exponential smoothing, Holt–Winter's additive, Holt–Winter's multiplicative, and ARIMA. After that, five different time series models are consolidated with six diverse consolidation methods, namely, SA, SATA, MB, VB, VBP2 and VBP3 in order to get a more robust stock price prediction model. Experiment results demonstrate that the utilization of the VBP2 consolidation technique presents remarkable results with 2.6903 of MAPE for estimating the price of the XUTEK index and 19 technology stocks.

1. Introduction

The Istanbul Stock Exchange defined as BIST 100 index, is a generally used abridgment of Turkey's stock exchange. ISE includes the index of national all stocks, the index of national 30 stocks, the index of national 50 stocks, the index of national 100 stocks, the indices of the sector and its sub-sectors, the index of the second national market, the index of the novel economy market and the index of investment trusts. The index of national 100 stocks covers both the index of national 50 stocks and the index of national 30 shares and is employed as a fundamental index of the national market of it. The technology index (XUTEK), which is covered by this study and contains 19 technology companies, is a sector index on the Istanbul Stock Exchange (BIST).

Stock price forecasting is an important and active research field for investors, researchers, and analysts. Stock prices are readily influenced by different external factors to contemplate, being complicated to acquire results with high accuracy due to their often complex and variable nature. Investors, analysts, and researchers assess their investments, analysis, and research with various parameters by conducting fundamental or technical analysis of them. The fundamental analysis investigates the value of an investment by exploring financial and economic elements while the movement direction of any investment is forecasted by employing various parameters such as volume, and price that is gathered from previous time periods of that investment. On the other hand, technical analysis is a method of predicting future prices based on information available in hand by employing past prices, volumes, and technical indicators to appraise the next movement in asset prices on historical data. In this work, we focus on technical indicators in order to forecast the price of the XUTEK index and technology stocks using time series models and a combination of them.

Time series forecasting is a statistical method of using a model to forecast future values based upon formerly observed time series values. It facilitates to analysis of patterns through time series are trend,

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seasonality, cyclicity, and irregularity. There are many application areas in time series analysis such as stock market analysis [1-2], economic forecasting [3-4], inventory studies [5-6], budgetary analysis [7-8], census analysis [9-10], yield projection [11-12], sales forecasting [13-14]. Utilizing time series analysis models such as simple exponential smoothing (SES), Holt–Winters (HW), Holt's linear trend (HLT), and autoregressive integrated moving average (ARIMA), it is proposed to comprehend the main elements giving a lead to the trend on the time series and perform a prudential stock price estimation.

In this work, we propose to predict the price of 19 technology stocks and the BIST Technology Index (XUTEK), which consists of 19 technology companies traded in BIST. Stock movements during the pandemic period between 01.01.2020 and 01.09.2020, when technology shares gained significant value, are investigated to estimate the price of the XUTEK. For 19 technology stocks and XUTEK index, five different time series models are modeled namely, simple exponential smoothing, Holt's linear trend, Holt–Winter's additive, Holt–Winter's multiplicative, and ARIMA. Finally, five different time series models are consolidated in order to get a more robust stock price prediction model. To our knowledge, this is the very first attempt in terms of consolidating time series models for the prediction of technology stocks and the XUTEK index in BIST during the pandemic period. Experiment results demonstrate that the combination of the time series model is an effective method to obtain robust results for forecasting the stock price of technology stocks and the XUTEK index instead of using individual forecasts.

The remaining article is designed followingly: Section 2 maintains an abstract of studies utilizing time series analysis. Section 3 includes time series analysis techniques presented under the proposed system. The proposed framework, the results of the experiments, discussion and conclusion sections are presented in Sections 4–6, respectively.

2. Related Work

A summary of the literature studies on time series analysis and different methods is presented to forecast the price or direction of different investment instruments. In financial markets, there are many studies that focus on making price forecasts of stocks, digital currencies, mineral commodities such as funds, gold, bonds, silver and such products.

In a study [15], authors propose to clarify the issue of macroeconomic prediction by defining whether generally well-accepted prediction methods that are commonly utilized to discover forecasts for Western macro economies are also helpful for China. These forecasting models include 19 different techniques which vary from straightforward methods to more complicated models namely, ARMA, Bayesian VAR, and factor models in order to estimate two distinct measures of price inflation and real activity. Authors conclude the study that AR, ARMA, VAR, and Bayesian VAR techniques ensure superior 1-month-ahead estimates of the producer price index when compared to basic models. In another study [16], the author aims to estimate Egyptian Exchange Price Index (EGX30) using vector autoregressive models (VARS). For this purpose, different versions of ARIMA and VAR models are carried out in the experiments. The author reports that five estimated values of all stationary time series, employing VARS (1) models, are forecasted.

In another study [17], authors propose to estimate the direction of the US Dollar/Turkish Lira exchange rate thereby combining deep learning methods and time series analysis. The combination of proposed model is based on time series analysis (TSA) and financial sentiment analysis (FSA). To conduct the FSA model, word embedding methods Word2vec, GloVe, fastText, and deep learning models such as CNN, RNN, and LSTM are employed. In order to construct the TSA model, simple exponential smoothing, versions of Holt-Winters, ARIMA models, and Holt's linear are utilized. They suggest that any user who wants to make a US Dollar/Turkish Lira exchange rate estimate using the proposed model can make a more consistent and strong exchange rate estimate. In a study [18], authors present a mixed model based on ARIMA and eXtreme gradient boosting (XGBoost) techniques to forecast the stock market volatility. The consolidation of ARIMA and XGBoost is performed by employing the discrete wavelet transform (DWT) approach. Experiment results show that the proposed hybrid method remarkably enhances the predictive performance of an individual ARIMA technique or an individual XGBoost method in forecasting stock prices. Pandey and Bajpai investigate the predictive efficiency of artificial neural network (ANN) and ARIMA approaches by evaluating Nifty Fifty in Indian Stock Market as a case study [19]. For this aim, the authors employ only closing, open, maximum and minimum data of indices as independent variables between January 2007 to December 2016. The paper is concluded that ANN exhibits better predictive performance in case of long span of time and nonlinear volatile series as of the Indian Stock Market Index NSE.

In addition to the usage of time series models, different models are also evaluated for forecasting the price or direction of any investment instrument. In a study [20], authors utilize the closing values of one, two, and three days ago, as well as the US Dollar rate, overnight interest rate and the Japanese Stock Exchange (NIKKEI), Brazilian Stock Exchange (Bovespa), UK Stock Exchange (FTSE), French Stock Exchange (CAC), German Stock Exchange (DAX) stock exchange index values between 2005 and 2012 to estimate the BIST100 index. Authors estimate the BIST index value using feed-forward artificial neural networks and support vector machine methods. As a result of the study, they note that stock market index forecasting with artificial neural networks and support vector machine methods yields significant results. In another similar study [21], it is indicated that the index value can be successfully modeled with feedforward neural networks using BIST data. In a study [22], it is proposed that a one-dimensional convolutional neural networks (CNNs) model predicts financial market movement, they evaluate the futures of six indices between 2010 and 2017. The results of the experiment demonstrate that the CNN model can effectively infer more generalized and informative features than traditional technical indicators and that more robust and profitable financial performance can be achieved from traditional machine learning approaches.

In another study [23], a new forecasting method using the temporal correlation between global stock markets and various financial products is presented to predict the next day's stock trend employing the support vector machine (SVM) method. The results are 74.4% of accuracy on the NASDAQ, 76% of accuracy on the S&P500 and 77.6% of accuracy on the DJIA. In a study [24], authors utilize the CNN-LSTM model to estimate the price of gold, which uses convoluted neural networks to extract useful information and learn the representation of time series data, as well as the effectiveness of long-short-term memory (LSTM) networks to identify short-and long-term dependencies. They report that the use of LSTM layers in conjunction with convolution layers can provide a significant increase in improving forecasting performance.

Moreover, there are many studies to analyze the BIST index during the pandemic period. In [25], the authors propose to investigate the effects of COVID-19 on the BIST-30 index in a short term. For this aim, daily prices between March 2020 and April 2020 are assessed. They report that Istanbul Stock Exchange demonstrates a negative reaction. In [26], Ilhan and Akdeniz focus on the importance of macroeconomic parameters on the stock market in Turkey during the pandemic period. The Flexible Least Squares technique is employed to observe the effect of the exchange rate, interest rate, CDS premium, oil and VIX prices on the BIST100 index between 2019 September and 2020 September. Authors conclude the study that all features investigated for impacts on the BIST100 have an importance during a pandemic period. In detail, it is also stated that CDS premium, and exchange rate exhibit a negative impact on BIST100. In [27], the reaction of the BIST 100 index against the Covid-19 pandemic is investigated. For this purpose, long and short-term estimations are performed employing robust and error correction models to analyze the impact of Covid-19 on BIST100 index. The rate of mortality, fair index, exchange rate, infectious diseases, volatility index, international equity index, and capital markets are evaluated as features of the proposed system. Experiment results indicate that features chosen for determining the effect of Covid-19 on the BIST 100 index are effective in both short and long term. In [28], Pakel and Ozen concentrate on daily volatility analysis of BIST 100 constituents between 2018 and 2020. To analyze the volatility of the daily revenues on stocks in BIST 100, the GARCH model is employed. The proposed model exposes that the volatility of the stock market has grown fairly during the periods in Turkey consolidated with two shocks, namely a currency and the Covid-19 pandemic. In [29], market risk premiums in BIST 100 in the COVID-19 pandemic period are studied. For this purpose, the dataset is gathered monthly through the Reuters database and the Central Bank of Turkey including BIST100 and 17 diverse sector indexes between 2019 and 2020. Authors conclude the study that the Covid-19 pandemic remarkably raises the volatilities and market risk premiums of the Turkish market.

3. Time Series Analysis

In this section, methods used in this work, including time series analysis models are briefly introduced. Time series analysis embraces the use of a number of statistical analysis methods in which the history is evaluated to make a significant deduction from the regular data coming through the time order, and to have an opinion of the future with predictive methods. Thus, the data acquired in time order are named time series. In other words, time series data implies that the data are gathered at a certain time period.

$$\{Y_t\} \ or \ \{Y_1,\ Y_2, \ldots Y_t\} \tag{1}$$

In Eq. (1), the time series gathered by a continuous and discrete period is demonstrated. The fundamental objective of time series analysis is to comprehend whether time impacts the variety in the value of X, which comprises the variable Y.

$$Y_t = \beta_0 + \beta X_t + u_t \tag{2}$$

where Y denotes the unit of time *t*, and Y_t implies the value that *Y* has picked up at time *t*. In Eq. (2), a two-variable dependent regression model beggared for a time series is stated. Because most machine learning models are not appropriate for running with missing values, the time series should be continual for these models to be employed efficaciously and favorably. To refrain from this issue, the incomplete values should be completed with the convenient data or the rows with the incomplete data should be removed. In this work, since technology stocks located in BIST100 at the weekends and holidays are not trading, the missing data is filled instead of deleting the lines that comprised the missing data, on condition that convenient data are available. For this reason, the missing values of weekends and holidays are filled in according to the closing values of the shares on the last trading day. In other words, the missing data for the weekend and holidays are filled in with the closing value of the last trading working day.

Simple exponential smoothing (SES) is a technique of exponential smoothing that gives exponentially downward weights based upon the recent and earliest samples from these data, utilized to forecast data that have no certain trend or seasonality [30]. Because simple exponential smoothing employs a weighted moving average with exponentially decrescent weights, it is convenient for short-term predictions although long-term estimates employing this method can be highly unfaithful.

$$S_t = \alpha y_t + (1-\alpha)S_{t-1} \tag{3}$$

where t implies to the time interval, y_t denotes current observation, S_t indicates the simple weighted average of y_t, and α demonstrates the smoothing constant, that is adjusted between 0 and 1 in Eq. (3).

Holt's linear trend method is a broadened model of the simple exponential smoothing technique. It is assumed that the trend is constant, continually enhancing or reducing in the future. This technique is carried out on data that are not seasonality but trend [31].

$$\hat{y}_{t+h|t} = \ell_t + hb_t \tag{4}$$

$$\ell_t = \alpha_{y_t} + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{5}$$

$$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \tag{6}$$

where ℓ_t indicates to the level in Eq. (4), Eq. (5), and Eq. (6), b_t implies the trend and α, $\beta*$ specify smoothing parameters.

The Holt-Winters seasonal model, also known as the triple exponential smoothing technique, is acquired by performing exponential smoothing three times. Essentially, the Holt–Winters method is a broadened model of Holt's linear trend model since a seasonal component is evaluated as an extra [32]. Different versions of the seasonality of this method are carried out with two different techniques namely, multiplicative and additive. The multiplicative method is opted provided that the seasonal modifications are constant throughout the time series, and providing that the seasonal modifications vary proportionally throughout the time series. The additive model is described in Eq. (7), Eq. (8), Eq. (9), and Eq. (10) as follows:

$$\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t+h-m(k+1)} \tag{7}$$

$$\ell_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{8}$$

$$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \tag{9}$$

$$s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \tag{10}$$

The multiplicative model is denoted in Eq. (11), Eq. (12), Eq. (13), and Eq. (14) as below:

$$\hat{y}_{t+h|t} = (\ell_t + hb_t)s_{t+h-m(k+1)} \tag{11}$$

$$\ell_t = \alpha\frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1}) \tag{12}$$

$$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \tag{13}$$

$$s_t = \gamma\frac{y_t}{(\ell_{t-1} - b_{t-1})} + (1-\gamma)s_{t-m} \tag{14}$$

where ℓ_t shows to the level, b_t demonstrates to the trend, α and $\beta*$ specify smoothing parameters, and m means the frequency of seasonality.

The most commonly utilized model in time series analysis and prediction is the autoregressive moving average (ARMA) method, along with the generalized autoregressive integrated moving average (ARIMA) model. Both methods are employed to better comprehend time series or to estimate the futurity values in time series. The ARIMA method consolidates the autoregressive (AR) and the moving average (MA) models to provide the time series stationary with a novel pre-processing stage named integration [33]. It is confessed that the future point of a variable is a linear function of previous samples and random errors in the autoregressive integrated moving average technique [34]. The ARIMA model comprises three several phases. The first stage is the value p (AR), the second phase is q (MA), and the last one is d(I), which is demonstrated as the weighted total amount of delayed forecasted errors of the time series. The ARIMA model is demonstrated in Eq. (15) as below:

$$ARIMA(p,d,q)$$

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i\, \varepsilon_{t-i} \tag{15}$$

where c represents the parameter interrupt that is predicted by the method. Φ and θ display the coefficient of delayed times forecasted by the method. μ is the expected point of X_t, X shows the delay value, and ε defines the randomly defined error variable.

4. Proposed Framework

In this section, data collection and proposed methodology are presented. In this work, stock movements during the pandemic period are proposed to analyze in order to forecast the price of the XUTEK index and 19 different technology stocks. For both 19 technology stocks and the XUTEK index, the values of the indicators that affect the direction of the technology index and stocks daily between 1 January 2020 and 1 September 2020, when technology shares gained significant value are collected. Indicators that are efficient in identifying the direction of the stocks and XUTEK index are collected via investing.com with the aid of Selenium library. The value of the "DayClass" parameter included in the features is obtained by subtracting the intraday opening value from the intraday closing value. If the resulting value is greater than 0, it is negative, if it is less than 0, the label value of that day is labeled positive. Some indicators of stocks are also added to the feature set to increase the feature diversity of the data set. These indicators consist of the 5, 10, 20, 50 and 100-day simple moving average (SMA), 14-day relative strength index (RSI) and the upper, middle and lower values of the Bollinger band. These indicators consist of the 5, 10, 20, 50,100 and 200-day simple moving average (SMA), relative strength index (RSI) and the upper, middle and lower values of the Bollinger band. Although there is no difficulty in gathering the opening and closing values of the technology stocks in the relevant date range via the Selenium crawler, the values of the technical indicators could not be obtained. For this reason, the technical analysis library named TA-lib [35] is used to obtain the historical indicator values and the values of the indicators mentioned above are calculated. The parameter details of the dataset to be used in the modeling are presented in Table 1.

Table 1. The parameter details of the 20 datasets.

Parameter	Explanation
Date	Date information
CloseP	Closing value of stock on that day
OpenP	Opening value of stock on that day
HighDay	The highest value of stock on that day
AvgDay	The average value of stock on that day
LowDay	The lowest value of stock on that day
DayClass	Value indicating whether the stock closed positive that day.
SMA_5	5-day simple moving average of the stock

Table 1. (Cont.) The parameter details of the 20 datasets.

Parameter	Explanation
SMA_10	10-day simple moving average of the stock
SMA_20	20-day simple moving average of the stock
SMA_50	50-day simple moving average of the stock
SMA_100	100-day simple moving average of the stock
SMA_200	200-day simple moving average of the stock
RSI	14-day Relative Strength Index of the stock
BollingerUpper	Top band value of daily Bollinger band for the stock
BollingerMiddle	Middle band value of daily Bollinger band for the stock
BollingerLower	Lower band value of daily Bollinger band for the stock

At the next step, 20 different datasets are ready to be modeled using simple exponential smoothing (SES), Holt's linear trend (HLT), Holt–Winter's additive (HWA), Holt–Winter's multiplicative (HWM), and ARIMA methods for 19 technology stocks and XUTEK index. Then, price forecasts for each technology stock and XUTEK index are acquired through the aforementioned models. Finally, five different time series methods are consolidated to acquire a final decision and a sturdier stock price prediction method. With this aim, 6 different combination techniques are assessed for linear forecasts. These are namely, simple average, simple average with trimming averages, median-based, variance-based, variance-based pooling with two clusters, and variance-based pooling with three clusters. All methods are appointed equal weights in the simple average approach (SA) [36-37] while individual estimates are consolidated simple arithmetic mean, excepting the worst n% of the methods in simple average with trimming averages (SATA) [36-37].

On the other hand, the consolidation function is the median of the individual estimates in the median-based (MB) consolidation method [38-39] while the ideal weights are assigned via the minimization of the total sum of squared error in the variance-based methodology (VB) [37, 40]. In variance-based pooling approach with clusters, previous performance is utilized group estimates into two (VBP2) or three clusters (VBP3) by a k-means technique as proposed in a study [41].

Finally, the best successful method is determined as a final decision among six different combination results in order to forecast the prediction of the XUTEK index and technology stocks in BIST during the pandemic period. To our knowledge, this is the very first work in terms of consolidating time series models for the prediction of the XUTEK index in BIST during the pandemic period. Experiment results demonstrate that the combination of the time series model is an effective method to obtain robust results for forecasting the stock price of technology stocks and the XUTEK index. In Figure 1, the architecture of the proposed framework is presented.

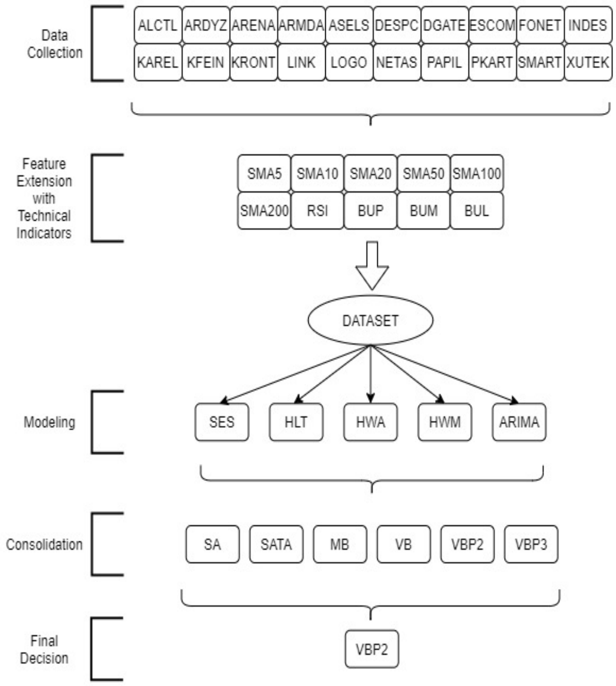

Figure 1. The architecture of proposed framework.

5. Experiment Results

In this study, comprehensive experiments are carried out to analyze the effectiveness of both combination of time series models and base time series methods for the estimation of XUTEK index and technology stocks in BIST during pandemic period. For empirical verification of forecasting performances of the proposed technique, twenty real world time series are employed as datasets that include XUTEK index and technology stocks in BIST100. Predicting success of all methods are evaluated with the well-known and widely-applied error statistics, viz the Mean Absolute Percentage Error (MAPE), mean absolute error (MAE), mean squared error (MSE), and R-squared (R^2) as defined below:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_a - y_f}{y_a}\right| \times 100 \tag{18}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_a - y_f\right| \tag{19}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_a - y_f\right)^2 \tag{20}$$

$$R^2 = 1 - \frac{\sum\left(y_a - y_f\right)^2}{\sum\left(y_a - y_m\right)^2} \tag{21}$$

where N is the size of test set, y_a and y_f are the actual and forecasted observations, respectively. The following abbreviations are utilized for the time series and consolidation models: SES: Simple exponential smoothing, HLT: Holt's linear trend, HWM: Holt–Winter's multiplicative, HWA: Holt–Winter's additive, ARIMA: Autoregressive integrated moving average, SA: Simple average approach, SATA: Simple average with trimming averages, MB: Median-based consolidation, VB: Variance-based consolidation, VBP2: Variance-based pooling approach with two clusters, VBP3: Variance-based pooling approach with three clusters. All techniques are implemented on Google Colab provided free GPU usage by Google.

Table 2. Forecasting mean absolute percentage error results of individual time series models in 20 datasets.

Dataset	Models				
	SES	**HLT**	**HWM**	**HWA**	**ARIMA**
ALCTL	3.425	3.351	3.169	3.095	2.993
ARDYZ	3.583	3.598	3.464	3.382	3.231
ARENA	3.441	3.403	3.381	3.350	3.271
ARMDA	3.473	3.451	3.442	3.440	3.352
ASELS	3.423	3.402	3.331	3.302	3.210
DESPC	3.455	3.413	3.425	3.403	3.251
DGATE	3.401	3.352	3.341	3.345	3.239
ESCOM	3.351	3.320	3.341	3.340	3.125
FONET	3.724	3.694	3.671	3.650	3.423
INDES	3.563	3.500	3.472	3.445	3.157
KAREL	3.254	3.227	3.200	3.179	2.897
KFEIN	3.389	3.352	3.341	3.317	3.054
KRONT	3.360	3.334	3.292	3.260	2.980
LINK	3.124	3.095	3.051	3.065	2.835
LOGO	3.270	3.210	3.184	3.154	2.893
NETAS	3.320	3.308	3.279	3.260	2.900
PAPIL	3.428	3.391	3.381	3.332	2.995
PKART	3.312	3.284	3.257	3.264	2.982
SMART	3.291	3.230	3.224	3.203	2.894
XUTEK	3.179	3.147	3.140	3.107	2.882
Average	3.388	3.353	3.319	3.295	**3.078**

The best performing MAPE scores are represented in bold. In Table 2 and Table 3, forecasting results of individual time series and consolidation models are presented in 20 datasets, respectively. In Table 2, MAPE results of five different time series models are demonstrated. It is clearly observed that average result for twenty datasets with 3.0786 of MAPE outperforms others. It is followed by HWA, HWM, HLT, SES, respectively. Moreover, ARIMA results of each dataset generally performs well for 20 datasets when the success of other techniques is considered. Among 20 datasets, XUTEK, SMART, NETAS, LINK, LOGO, and KAREL stocks exhibit more successful MAPE results in terms of ARIMA performance.

On the other hand, it is obviously seen that SES model presents the poorest success with 3.3886 of average MAPE. Thus, SES model is not convenient to estimate both the price of XUTEK index and technology stocks. When average MAPE scores are considered, HLT method maintains 0.03 improvement. On the other hand, HWM model provides 0.07 enhancement in difference between error statistic in comparison with the performance of SES. In addition, ARIMA shows 0.31 progress while HWA model presents 0.09 improvement compared to the SES. Enhancement in MAPE of ARIMA model is clearly observed with 0.31 difference. Hereby, ARIMA as an individual technique is convenient to estimate the price of XUTEK index and 19 technology stocks in BIST100.

Table 3. Forecasting mean absolute percentage error results of consolidation models in 20 datasets.

Dataset	Models					
	SA	SATA	MB	VB	VBP2	VBP3
ALCTL	2.840	2.834	2.795	2.881	2.653	2.692
ARDYZ	3.085	3.081	3.021	3.112	2.852	2.897
ARENA	3.114	3.101	2.782	3.143	2.641	2.684
ARMDA	3.203	3.193	3.157	3.247	2.995	3.057
ASELS	3.021	3.019	2.964	3.079	2.812	2.856
DESPC	3.062	3.058	3.001	3.135	2.854	2.890
DGATE	3.054	3.048	2.982	3.107	2.831	2.874
ESCOM	2.952	2.943	2.891	3.019	2.755	2.780
FONET	3.193	3.185	3.139	3.273	2.994	3.056
INDES	2.992	2.989	2.941	3.048	2.792	2.840
KAREL	2.684	2.680	2.635	2.771	2.501	2.546
KFEIN	2.900	2.889	2.854	2.940	2.703	2.754
KRONT	2.823	2.817	2.779	2.875	2.630	2.690
LINK	2.662	2.653	2.601	2.723	2.468	2.511
LOGO	2.683	2.680	2.645	2.774	2.492	2.537
NETAS	2.741	2.735	2.699	2.790	2.539	2.580
PAPIL	2.830	2.828	2.772	2.863	2.630	2.691
PKART	2.801	2.793	2.753	2.854	2.624	2.674
SMART	2.730	2.725	2.684	2.781	2.531	2.578
XUTEK	2.713	2.710	2.650	2.767	2.500	2.560
Average	2.904	2.898	2.837	2.959	**2.690**	2.737

In Table 3, forecasting results of consolidation models for XUTEK and 19 technology stocks are presented. It is obviously seen that all consolidation models remarkably excel all individual models in terms of forecasting the price of stocks and technology index when mean MAPE results are considered. Even the poorest consolidation model VB shows a 2.9595 MAPE value which means nearly 0.12 enhancement while the best individual models ARIMA exhibits a 3.0786 MAPE result. It is followed by 2.90 with SA, 2.89 with SATA, 2.83 with MB, 2.73 with VBP3, and 2.69 with VBP2.

The utilization of variance-based polling techniques remarkably provides enhancement compared to the other consolidation techniques. When the overall MAPE performance of VBP2 is observed, it demonstrates less MAPE compared to other models. The performance order between consolidation models can be summarized as VBP2> VBP3> MB> SATA> SA> VB. VBP2 technique ensures approximately 0.04, 0.14, 0.2, 0.21, 0.26 advancement in MAPE results compared to VBP3, MB, SATA, SA, VB, respectively. As a result of Table 2 and Table 3, VBP2 as a consolidation technique is more convenient with almost 2.69 MAPE value to forecast the price of the XUTEK index and 19 technology stocks in BIST100. Moreover, different evaluation metrics, namely MAE, MSE, and R^2 are presented in addition to MAPE values for the best prediction model VBP2 in Table 4.

In Figure 2, the actual price, the best predicted individual time series and consolidated models are compared for six datasets namely, XUTEK, SMART, NETAS, LOGO, LINK and KAREL. Black, red, and blue lines demonstrate the actual price, VBP2 prediction, and ARIMA estimation of the stocks, respectively. It is obviously observed that VBP2 exhibits remarkable experiment results during the pandemic period because it exhibits very close performance to the actual price of each dataset. On the other hand, ARIMA as an individual time series model is not capable to forecast the XUTEK index and technology stocks as much as VBP2 for each dataset although ARIMA outperforms other individual time series techniques.

Table 4. MAPE, MAE, MSE, and R2 results of VBP2 consolidation model in all datasets.

Dataset	Evaluation Metrics			
	MAPE	MAE	MSE	R^2
ALCTL	2.6530	0.0114	0.0032	0.9971
ARDYZ	2.8522	0.0145	0.0055	0.9929
ARENA	2.6415	0.0127	0.0028	0.9983
ARMDA	2.9952	0.0162	0.0076	0.9827
ASELS	2.8123	0.0140	0.0047	0.9975
DESPC	2.8540	0.0149	0.0058	0.9931

Table 4. (Cont.) MAPE, MAE, MSE, and R2 results of VBP2 consolidation model in all datasets.

Dataset	Evaluation Metrics			
	MAPE	**MAE**	**MSE**	**R^2**
DGATE	2.8315	0.0138	0.0031	0.9935
ESCOM	2.7550	0.0133	0.0044	0.9980
FONET	2.9948	0.0173	0.0073	0.9836
INDES	2.7925	0.0135	0.0052	0.9980
KAREL	2.5013	0.0079	0.0018	0.9989
KFEIN	2.7037	0.0129	0.0045	0.9984
KRONT	2.6309	0.0130	0.0025	0.9985
LINK	2.4688	0.0027	0.0012	0.9989
LOGO	2.4927	0.0045	0.0026	0.9989
NETAS	2.5394	0.0068	0.0034	0.9988
PAPIL	2.6302	0.0142	0.0020	0.9987
PKART	2.6240	0.0123	0.0014	0.9986
SMART	2.5319	0.0071	0.0025	0.9988
XUTEK	2.5006	0.0067	0.0015	0.9988
Average	**2.6903**	**0.0114**	**0.0036**	**0.9961**

As a result of this work, the consolidation of time series models performs well to estimate the price of the XUTEK index and 19 technology stocks in BIST100. It is clearly observed that usage of consolidation models performs better than traditional time series methods. Even the poorest performance of consolidation model VB excels the best individual time series model ARIMA. For this reason, the VBP2 consolidation model is convenient to estimate the price of the XUTEK index during the pandemic period. It is hard to compare the success of our results with other studies because of the lack of works with similar combinations of different methods, datasets, and consolidation approaches. Although a comparison of baseline time series models and consolidation techniques is given in this work, we also report the MAPE results of several works here.

In a study [16], it is proposed to forecast Egyptian Exchange Price Index (EGX30) using different versions of ARIMA. The author reports that the best MAPE result of the ARIMA model is obtained as 5.9954 while our ARIMA method exhibits a 3.0786 MAPE value. Moreover, the best consolidation method of this study (VBP2) presents 2.6903 of MAPE which demonstrates the success of our proposed system compared to the literature study [16]. In another work [17], the authors aim to forecast the direction of the US Dollar/Turkish Lira exchange rate by combining time series analysis and deep learning methods. Authors report MAPE results as 2.6432 for SES, 2.4576 for HLT, 2.6325 for HWM, 2.6273 for HWA, and 2.7144 for ARIMA while MAPE results in this study are 3.3886 for SES, 3.3535 for HLT, 3.3197 for HWM, 3.2951 for HWA, and 3.0786 for ARIMA model. This can arise in different experiment settings, datasets, number of features, and attributes. The same models exhibit a more successful performance in the study [17], while the proposed hybrid model in this work, namely VBP2 outperforms all models with 2.6903 of MAPE result. In a study [37], authors present a meta-learning approach for time series forecasting and consolidation of them employing SA, SATA, VB, VBP2, and VBP3 methods. Because they report experiment results using symmetric MAPE (sMAPE) results, we also calculate the sMAPE results of all consolidation methods used in this work in order to compare the success of models. Lemke and Gabrys report the sMAPE results for consolidation models as 17.5 for SA, 17.4 for SATA, 18.1 for VB, 16.4 for VBP2, 16.8 for VBP3 while sMAPE values in this work are 17.1 for SA, 16.9 for SATA, 16.4 for MB, 17.7 for VB, 15.6 for VBP2, and 15.9 for VBP3. This demonstrates that our proposed consolidation model, VBP2 exhibits similar performance to the study [37] by obtaining the best sMAPE result compared to the other models. As a result, it is obviously observed that the consolidation of time series models is an efficient way for the purpose of forecasting the XUTEK index and technology stocks in BIST during the pandemic period.

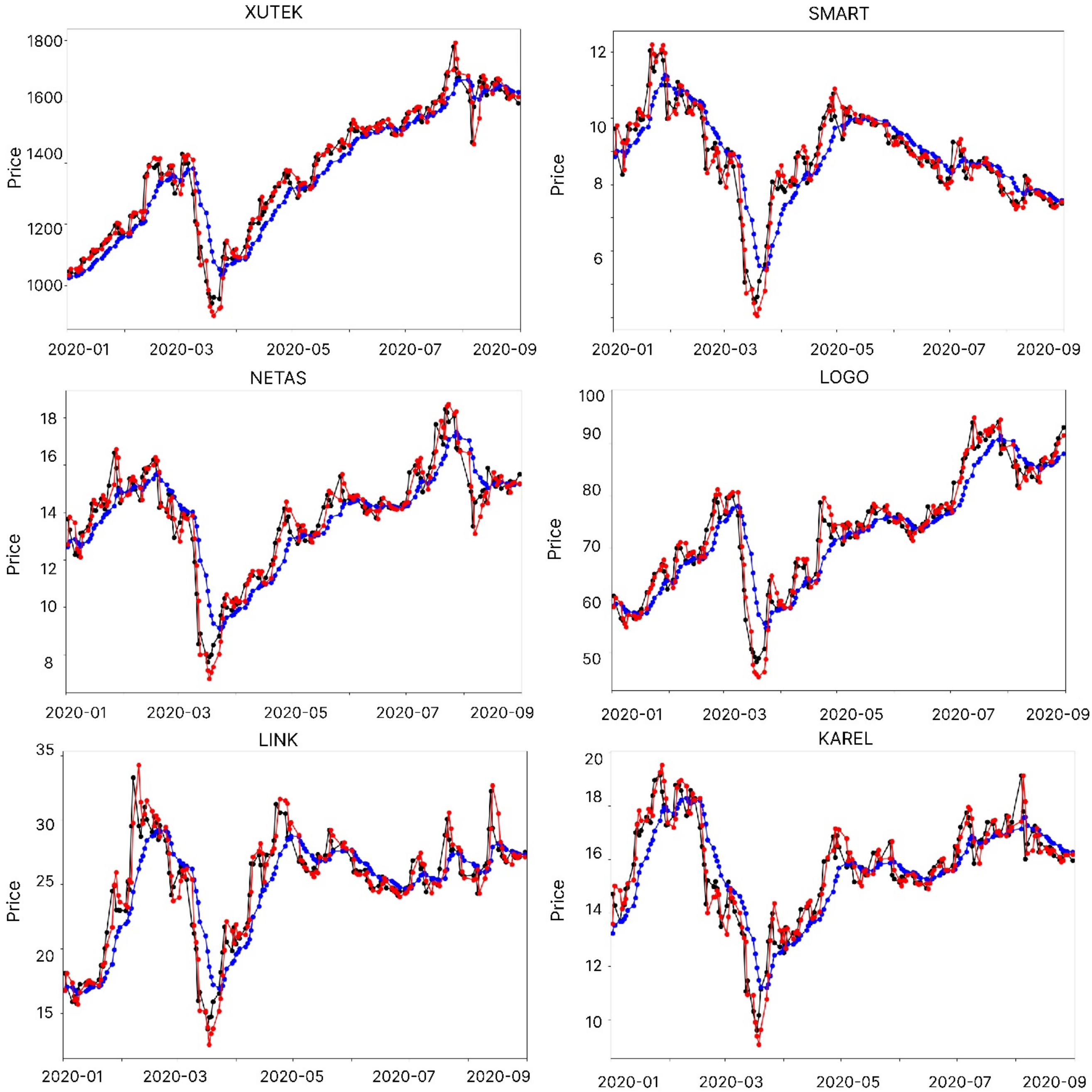

Figure 2. The comparison of actual price, forecasted prices of ARIMA (the best individual model), and VBP2 (the best consolidation model).

6. Discussion and Conclusion

Due to the closure experienced during the pandemic, many investors direct their investments to different exchanges. It is seen that while sectors such as transportation, banking, and services have seriously lost value, especially the technology sector has come forward and gained value. In this work, we propose a consolidated forecast system to forecast the price of the technology Index (XUTEK) which consists of 19 technology companies traded in BIST, and technology stocks in BIST. Stock movements during the pandemic period between 01.01.2020 and 01.09.2020 are analyzed in order to estimate the price of XUTEK and stocks. For each technology stock, and XUTEK index, five different time series models are evaluated namely, SES, HLT, HWA, HWM, and ARIMA. Then, five different time series models are combined with six consolidation methods, namely, SA, SATA, MB, VB, VBP2, VBP3 in order to get a more robust stock price prediction model. Finally, the VBP2 technique outperforms both conventional time series models and consolidation methods. Comprehensive experiment results demonstrate that the proposed consolidation model exhibits notable scores for estimating the price of the XUTEK index and 19 technology stocks. In the future, we plan to cover various fundamental and technical indicators to broaden the feature space for the purpose of boosting the performance of the system.

Declaration of Ethical Standards

The author of this article declares that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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