New Model for Stock Price Prediction Using Hybrid Approach of EEMD and ARIMA

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Abstract

This paper tries to use hybrid model ensemble empirical mode decomposition to predict stock prices in Tehran Stock Exchange. In order to achieve this goal, EEMD model is coupled with one of the mean time series model econometrics autoregressive integrated moving average (ARIMA). Data Coverage in this paper is weekly stock price of Mobarakeh Steel Company for period of July 2011 to August 2016. At first the EEMD method is used to decompose the original stock price into several intrinsic mode function (IMF), then ARIMA models are considered to each IMFs. Finally, sum of each IMFs forecasting results will be the final stock price prediction. To justify the performance of developed hybrid model, it's prediction were compared with ARIMA and it was found that the suggested model, compared to ARIMA, in rescheduling, is better for prediction with less error in its price forecast in terms of root mean squared error (RMSE), mean absolute percentage error (MAPE), and directional symmetry (DS).

Keywords: Stock Price, Prediction, Time Series, EEMD, ARIMA.

Introduction

Financial researchers and investors are always looking for forecasts and the behavior of stock prices in the stock market. The most important reason for investing in the stock market is to make a profit which needs to the right information from the market, stock changes and future trends. Hence, investors are looking for using the powerful and reliable tools through which it can pay to predict the correct stock prices. Increasing shareholders and their attention to stock prices prediction, has made it very important.

The stock market is influenced by several factors including economic and political factors, the large number of unknown factors in this market which has created the inevitable uncertainty in the investment field. Investors are always looking for ways to be able to have better forecasts, more accurately and with fewer errors, than their price trend, the selection and optimization modeling, and facilitate decision-making process in the stock market. Thus, the stock market has long been the focus of attention, and so far, different methods have been proposed to predict.
However, these methods, to some extent, increase forecast accuracy but in most ways, the overall stock prices and known factors, affect the price for the anticipated use; if the stock market and as well as stock quotes, including several who are taking advantage of the new tools of analysis, such as Ensemble Empirical Mode Decomposition (EEMD), stock prices can be decomposed into components and used it for prediction. Decomposition of EEMD, in order to investigate the behavior of nonlinear and non-stationary time series, is a replacement tool for researchers which can describe the time-series analysis and time series of smaller and independent series in a different way. As recent studies have shown, financial markets, as usual, are non-linear and non-stationary (Thomaidis, 2007) and this distinctive feature have made valuable and attractiveness of this way, as a tool to predict stock price.

So according to what was said, the aim of this study is to use a new methodology for predicting stock prices using Ensemble Empirical Mode Decomposition (EEMD) and time series models. Previous observations in time-series models, a variable were used to develop the model and predict the future. The model assumes that all factors and effective communication in the formation of a variable and its values are represented. So, we can predict the only variable studied based on previous data. Autoregressive Integrated moving Average (ARIMA) is one of the most time-series models. The main objective of this research is to design and provide a model to predict stock price, using a combination of EEMD and ARIMA, and comparing the accuracy of forecasts and setting the correctness to predict this model with other models.

In the research model, the weekly stock price of Mobarakeh Steel Company is used to review the research model. First, using EEMD, time series of the study is decomposed into several intrinsic mode function (IMF). Each of the IMFs is with different nature and characteristics and each one is modeled with the ARIMA. After sizing up the optimized model, their predicted future values have been calculated, and finally, the results of the combined IMF are predicted and finally the predictions for Mobarakeh Steel's share price are achieved. To verify the accuracy and performance prediction, Mobarakeh Steel share prices is forecast by ARIMA model, and the results of these two models are predicted and compared using performance metrics root mean square error (RMSE), mean absolute percentage error (MAPE), the symmetry direction (DS) and the optimal model will be selected.

The structure of the research is that in the second part the related research will be checked briefly. The third section focuses on the study model used in the study on the proposed model. In the fourth section, the data used in the study are introduced and the fifth part, the results of the model will be expressed. Finally in sixth part, conclusions of research are presented.

The Research literature

The empirical mode decomposition (EMD) and the ensemble empirical mode decomposition (EEMD), as a method of scientific analysis, have been developed in most cases, the results are satisfactory. EMD and EEMD have many applications in many fields including: Vincent et al (1999), for seismic signal analysis and analysis of bridge and structure have used EMD; Guo et al (2012) using EMD and then prediction using a neural network, have analyzed the series of wind speed; Chen et al (2012), using a hybrid approach of EMD with an artificial neural network have forecasted tourism demand and Yu (2005) for device error detection have used this method.

Although this method has very interesting properties, yet it has not applied in financial applications. Although various methods of research have been done in the field of forecasting stock prices, but in this section, it is dumped into articles in which, using methods of the research, have predicted the stock price.

The research was conducted in 2008 by Zhang et al to predict the price of crude oil using EMD and Forwarded Neural Network, which indicated the superiority of this method.

Lin et al (2012), in their paper paid to exchange rates time series forecasting from 2005 to 2009, using a combination of LSSVR and EMD. Due to the nonlinear and non-stationary of the series, they took advantage of the algorithm EMD for analysis, the results of the evaluation criteria MAPE, RMSE, MAD showed that the proposed hybrid model is better than ARIMA, LSSVR methods.

In another paper, Premanode and Toumazou (2013), for improving the prediction of exchange rate, provided the combination of differential EMD and SVR, which results are indicative of the superiority of the proposed model than the MS-GARCH and Markov switching regression (MSR).

Feng et al (2013), used empirical mode decomposition and ARIMA, forecasted the Dow Jones stock. Using the analysis, time series were predicted, the IMF produced by the decomposition series, using ARIMA, which by its composition, forecasts were finalized, and for comparison with real data, not much difference.

Cheng and Wei (2014) selected support vector for empirical mode decomposition to predict the combined method (EMD) and regression to check the accuracy of the results, forecasting autoregressive model and supporting vector regression. The evaluation criteria RMSE in this period for the hybrid model, acts with fewer errors than other methods.
Chengzhao and Heiping (2015), checked the accuracy of forecasts for the combination model of empirical Mode Decomposition (EMD), and neural network. The sample in this article resembles three stock market index of Asia, in the period of 2005 to 2014 in the results of the superiority analysis model, compared to the neural network. Abadan and Shabri (2014), for predicting the price of rice in Malaysia, have used empirical mode decomposition method (EMD), and combine it with ARIMA. Analysis of IMF forecasts obtained from ARIMA and composition, the price of rice was achieved anticipated results. Benchmark of RMSE, showed the accuracy of the method is a combination EMD-ARIMA, and compared with ARIMA.

Plakandaras et al (2015) in his paper evaluated the cause of a sudden drop in housing prices in America, in 2006 and decided to present a new method, which is the lowest prediction error. Used combined method empirical mode decomposition method batch (EEMD) and SVR. EEMD methods, due to lack of combination frequencies and the attention, and with the IMF predicted by the SVR, were obtained better results.

Yang and Lin (2016), in his paper, elected empirical mode decomposition method (EMD), support vector regression (SVR) and ARIMA, to forecast daily, four stocks in India, from 2002 to 2010, the proposed model in the DS evaluation criteria and MAPE, better results than ARIMA models and SVR.

The reviewed studies indicates that according to the research that has been done in the field of forecasting stock prices, combined approaches deliver better results with higher accuracy. According to studies conducted so far, research using EEMD, has not been used in Iran, in the financial sphere. The aim of this study is to provide a new approach to predict stock prices, using empirical mode decomposition batch, and ARIMA. The next section is the theoretical basis of the model used in this study.

Research Model

This section is an overview of the methodology of this paper, which included empirical mode decomposition method, empirical mode decomposition batch and ARIMA model.

Empirical mode decomposition (EMD)

There are several ways to decompose time series in which the most important of them include STFT (Short-Time Fourier Transform) and wavelet transform, which using short-time Fourier, turns out time series into a series of sinusoidal functions with different frequencies, with a series of windows. Given the shortcomings of this method, the wavelet transform has been introduced. Wavelet transform to decompose non-stationary time series, was welcomed that, using a mother wavelet function, time series, could be divided into different sections. Given that, in the wavelet transform, mother wavelet functions are used to analyze series, suitable mother wavelet detection, is time consuming and complicated. Therefore, empirical mode decomposition method (EMD), was introduced by Huang et al in 1998. This data analysis is a scientific tool to get input component, which is a good tool to analyze data from non-viable and non-linear. In this way, based on a process, the signal can be decomposed into several intrinsic mode functions (IMF), which are oscillatory wave series, with an average of zero. The basic functions are waves that have been extracted from the signal. In this way, unlike other existing methods, no pre-set filter is used. Using obtained intrinsic modes, the signals can be restored.

Intrinsic mode function or experimental mode function is the function that meets the two following conditions:
1) In general, the number of extreme points and the number of zero-crossing points, should be equal or at least has a point of difference. 2) At each point, the average envelope of the maximum and minimum should be zero.

The steps of empirical mode decomposition signal \(x(t)\), to obtain intrinsic mode functions are as follows:

Identify all the local maxima and minima of time series.
Connect the local maxima (minima) by a cubic spline to define the upper (lower)
Average upper and lower envelop is calculated which is characterized by \(m_1\). In figure 1, upper and lower envelop and mean values, for signal \(x(t)\) is shown.

The difference of \(x(t)\) and \(m_1\) are calculated that is called prototype of the first intrinsic mode function of \(h_1\). Equation 1 shows this relationship.

\[ h_1 = x(t) - m_1 \]

If \(h_1\) has the conditions of an intrinsic mode function, it will be selected as the first intrinsic mode function, otherwise, the first and fourth stages which are known as the sifting will be repeated on \(h_1\), \(k\) times, so that when
$h_{lk}$ is a function of inherent mood, will be obtained according to equation 2.

$$h_{l(k-1)} - m_{lk} = h_{lk} \quad 2$$

To ensure that given the inherent modes fully meet the above requirements, it is necessary to consider stop condition in repeat process. Equation 3 shows the condition of the stop.

$$SD = \sum_{t=0}^{T} \left[ \frac{[h_{l(k-1)}(t) - h_{l(k)}(t)]^2}{h_{l(k-1)}^2(t)} \right] \quad 3$$

When stopping criterion is smaller than a certain amount, screening action stops and $h_{lk}$ will be displayed as the first intrinsic mode function, with $c_1$. In fact, $c_1$ is the higher frequency components of the signal? By subtracting $x(t)$ signal the remaining amount will be obtained according to Equation 4.

$$x(t) - c_1 = r_1 \quad 4$$

Because remaining amount is still contained low-frequency data, the new data will be considered and the screening is done again to extract the next natural mood (steps 1 to 6). This process is repeated for subsequent remaining as equation 5.

$$r_1 - c_2 = r_2, r_{n-1} - c_n = r_n \quad 5$$

This process stops when $r_n$ becomes a smooth function or single-frequency signal, and no single frequency component be extractable. Finally, the relationship between isolated and signal mode would be as the 6 equation:

$$x(t) = \sum_{i=1}^{n} c_i + r_n \quad 6$$

Which indicates that $x(t)$ signal is decomposed in to intrinsic mode function and the remaining $r_n$ (Huang et al., 1998).

![Figure 1](image.png)

**Figure 1.** Black: signal curves, green: average maximum and minimum envelop curve, Blue: average envelop curve (Huang et al., 1998).

**Ensemble Empirical Mode Decomposition**

Because of the difficulty in mode mixing in the empirical mode decomposition method (EMD), Wu and Huang
in 2009 introduced Ensemble Empirical Mode Decomposition (EEMD), which by adding noise to the signal this problem is partly solved (Wu & Huang, 2009).

**EEMD algorithm consists of the following steps**

Addition of white noise \( w_j(t) \) to the considered time series of \( x(t) \) according to Equation 7

\[
x_j(t) = x(t) + w_j(t)
\]

7

Decomposing time series, with \( x_j(t) \) added noise, by way of EMD to IMFs, according to Eq. 8

\[
x_j(t) = \sum_{j=1}^{n} \bar{c}_j + r_{jm}
\]

8

M times repetition of 1 and 2 steps, with different white noise and obtains new IMF, according to Eq. 9

\[
x_j(t) = \sum_{j=1}^{n} \bar{c}_j + r_{jm}
\]

9

Calculating the mean IMF and remaining as the final answer, as Eq. 10

\[
\bar{r}_j = \frac{1}{m} \sum_{i=1}^{m} r_{jm}
\]

\[
\bar{c}_j = \frac{1}{m} \sum_{i=1}^{m} c_{ij}
\]

10

Finally, the relationship between isolated fashion and data by EEMD is as Eq.11 (Wu & Huang, 2009):

\[
x(t) = \sum_{j=1}^{n} \bar{c}_j + \bar{r}_j
\]

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**Autoregressive integrated moving average Model (ARIMA)**

Autoregressive integrated moving average model is shown usually as ARIMA \((p, d, q)\) form in which \( p \) is the order of Autoregressive, \( d \) is the difference order for stabilizing time series and \( q \) is the order of moving averages. In this way, to predict future values of variables, to predict the values of previous variable, it can be used the present and the past and disrupting components. To stabilize the financial time series, differencing method is used often. So, if a time series, after a few times of differencing, gets stabilized, it would be modeled by the ARMA \((p, q)\). ARMA Model, for the time series of \( Y_t \) is as equation 12 (Brooks, 2008):

\[
Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \mu_t + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \ldots + \theta_q \mu_{t-q}
\]

12

After reviewing stationary series, model order should be recognizable. To obtain \( p \) and \( q \) it can be used both Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) and also information measures. After the identification process orders Autoregressive and moving average model parameters, by the least squares method, or other methods, such as Maximum Likelihood, it is estimated. At this point, after selecting the ARIMA model, independence of residuals should be tested. Auto Regressive Integrated moving Average is the optimal model, its residues, have not linear correlation. Finally, using the estimated parameters, and model data, and identify Autoregressive Integrated moving Average fitted predict the next observation (Brooks, 2008).
The hybrid model

In this study, by using time series method of EEMD, weekly data of Mobarakeh Steel stock prices has been decomposed into some IMF, which each IMF is a feature. The IMF Board, which has high frequencies, are indicative of the impact of rumors and happenings detail, on the stock market price. The next IMF, the less frequently they are more stable and long-lasting effect macro events, in the stock market and economic situation on the price (such as interest rate hike by the central bank). The last IMF shows the general trend of the share price. Next, each of the series of IMF is predicted by the model ARIMA. Finally, the results from each of the IMFs forecast, combined with each other, to be sure, predicting the final price of Mobarakeh Steel. The hybrid model is shown in Figure 1.

![Diagram](https://via.placeholder.com/150)

**Figure 1.** Process analysis and time series forecasting for share price (Sin Lin, 2012).

Methodology

In this study, using hybrid model EEMD and ARIMA, it was provided a more accurate prediction model for stock prices. Data and time period of this study include Mobarakeh Steel company weekly prices, from July 2011 to August 2016 (267 Views) in which, 247 first observations are used for sizing up the model, and next 20 observations are used for comparing the performance of prediction accuracy as rolling window. To verify the accuracy of forecasting performance of hybrid model, the results are compared with the ARIMA. According to the projections made for twenty weeks ahead, performance evaluation criteria, root mean square error (RMSE), and mean absolute percentage error (MAPE), and to determine the accuracy of the forecast, symmetry criteria for (DS), for each week, and both models are used. These three criteria are calculated as equations 13, 14 and 15.

\[
RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (p_t - \hat{p}_t)^2}
\]

\[
MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{p_t - \hat{p}_t}{p_t} \right| \times 100
\]
Where

\( p_i \): The actual value of the variable at time \( t \)

\( p_i \): The amount of variable variance at time \( t \)

In Table 1, test results of generalized Dickey Fuller (ADF) is shown. As it is clear from the amount of \( p \)-Value of this test, Mobarakeh steel price series were non-viable at 95%, and is the perfect combination method.

**Table 1. Test results of generalized Dickey Fuller (ADF).**

<table>
<thead>
<tr>
<th>Share</th>
<th>H</th>
<th>p-Value</th>
<th>t-statistic value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobarakeh Steel Company</td>
<td>0</td>
<td>0.818</td>
<td>0.482678</td>
</tr>
</tbody>
</table>

**Results**

According to what has been said in previous sections, a new approach was introduced to predict the Mobarakeh Steel shares using a combination of EEMD and ARIMA. In this area of research dealt with the analysis of results. To make forecast for 248th observation of stock price (in the third week of March 2016) by the proposed model, initially, weekly data of Mobarakeh Steel shares, from mid-July 2011 to mid-March 2016, totally 247 observations, using EEMD were decomposed in to 5 IMF. In Figure 2, the figure of IMFs of Mobarakeh Steel prices related to the series are depicted.

**Figure 2. Decomposition of Mobarakeh Steel Company.**

After decomposition of the share price of steel Company, each of the IMF’s would be forecasted using ARIMA, and then we combine these projections together and thus, predicting the final price of Mobarakeh Steel will be obtained. To predict ARIMA, it is necessary to check stationary of each of IMF, using generalized Dickey-Fuller test. Table 2 shows, generalized Dickey Fuller test results for the first IMF forecast period of steel company shares.
Table 2. Dickey Fuller unit root test for the IMFs of Mobarakeh Steel Company.

<table>
<thead>
<tr>
<th>IMF</th>
<th>H</th>
<th>p-Value</th>
<th>t-statistic value</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMF1</td>
<td>1</td>
<td>0.001</td>
<td>-14.8443</td>
</tr>
<tr>
<td>IMF2</td>
<td>1</td>
<td>0.001</td>
<td>-4.52342</td>
</tr>
<tr>
<td>IMF3</td>
<td>0</td>
<td>0.086</td>
<td>-1.69189</td>
</tr>
<tr>
<td>IMF4</td>
<td>0</td>
<td>0.23</td>
<td>-1.12887</td>
</tr>
<tr>
<td>IMF5</td>
<td>0</td>
<td>0.553</td>
<td>-0.25455</td>
</tr>
<tr>
<td>Residue</td>
<td>0</td>
<td>0.999</td>
<td>2.663119</td>
</tr>
</tbody>
</table>

As it is indictable from the table of Dickey Fuller test, 1 and 2 IMF at 95% are stable and the remainder were non-viable in which, to make steady them, differencing method would be used.

For modeling ARIMA, after stabilizing IMF, it was determined Autoregressive orders and moving averages for each of the IMFs individually, and on the basis of Schwarz Bayesian. After determining the optimal intervals for each of the IMF, the model parameters were estimated. Table 3 shows the results of the ARIMA model.

Table 3. The results of ARIMA model for the IMFs of Mobarakeh Steel Company.

<table>
<thead>
<tr>
<th>IMF</th>
<th>ARIMA(p,d,q)</th>
<th>$\varphi_p$</th>
<th>$\theta_q$</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMF1</td>
<td>2,0,1</td>
<td>0.5617, -0.4182</td>
<td>-0.6371</td>
</tr>
<tr>
<td>IMF2</td>
<td>4,0,1</td>
<td>2.3144, -2.5063, 1.4321, -0.4022</td>
<td>0.5532</td>
</tr>
<tr>
<td>IMF3</td>
<td>3,1,1</td>
<td>1.7733, -0.8915</td>
<td>1.2212, 0.5723</td>
</tr>
<tr>
<td>IMF4</td>
<td>1,2,1</td>
<td>0.9807</td>
<td>0.8763</td>
</tr>
<tr>
<td>IMF5</td>
<td>1,0,1</td>
<td>-0.0048</td>
<td>-0.0052</td>
</tr>
<tr>
<td>Residue</td>
<td>1,2,0</td>
<td>0.987</td>
<td>-</td>
</tr>
</tbody>
</table>

After selecting the optimal ARIMA model, each of the IMF's was forecasted for a period ahead. Finally, by combining these projections with each other, Mobarakeh Steel weekly share price was forecast using EEMD and ARIMA. Anticipated results for 248th observation, along with the IMF, are shown in Table 4.

Table 4. Results of the proposed method of predicting of Mobarakeh Steel price.

<table>
<thead>
<tr>
<th>IMF</th>
<th>Prediction result</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMF1</td>
<td>23</td>
</tr>
<tr>
<td>IMF2</td>
<td>26</td>
</tr>
<tr>
<td>IMF3</td>
<td>83</td>
</tr>
<tr>
<td>IMF4</td>
<td>121</td>
</tr>
<tr>
<td>IMF5</td>
<td>-310</td>
</tr>
<tr>
<td>Residue</td>
<td>1453</td>
</tr>
<tr>
<td>Steel price</td>
<td>2017</td>
</tr>
</tbody>
</table>

Table 5 shows the results of Weekly forecast of steel prices, from mid-March 2016 to July 2016 with two ways:
Table 5. Forecast results for twenty weeks ahead of Mobarakeh Steel Company stock.

<table>
<thead>
<tr>
<th>Anticipated results of Mobarakeh Steel</th>
<th>ARIMA</th>
<th>EEMD-ARIMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1437</td>
<td>1396</td>
</tr>
<tr>
<td>2</td>
<td>1429</td>
<td>1394</td>
</tr>
<tr>
<td>3</td>
<td>1333</td>
<td>1266</td>
</tr>
<tr>
<td>4</td>
<td>1357</td>
<td>1412</td>
</tr>
<tr>
<td>5</td>
<td>1359</td>
<td>1400</td>
</tr>
<tr>
<td>6</td>
<td>1373</td>
<td>1371</td>
</tr>
<tr>
<td>7</td>
<td>1316</td>
<td>1268</td>
</tr>
<tr>
<td>8</td>
<td>1280</td>
<td>1216</td>
</tr>
<tr>
<td>9</td>
<td>1247</td>
<td>1197</td>
</tr>
<tr>
<td>10</td>
<td>1239</td>
<td>1194</td>
</tr>
<tr>
<td>11</td>
<td>1208</td>
<td>1184</td>
</tr>
<tr>
<td>12</td>
<td>1187</td>
<td>1161</td>
</tr>
<tr>
<td>13</td>
<td>1129</td>
<td>1143</td>
</tr>
<tr>
<td>14</td>
<td>1108</td>
<td>1195</td>
</tr>
<tr>
<td>15</td>
<td>1194</td>
<td>1220</td>
</tr>
<tr>
<td>16</td>
<td>1197</td>
<td>1234</td>
</tr>
<tr>
<td>17</td>
<td>1269</td>
<td>1192</td>
</tr>
<tr>
<td>18</td>
<td>1216</td>
<td>1254</td>
</tr>
<tr>
<td>19</td>
<td>1232</td>
<td>1316</td>
</tr>
<tr>
<td>20</td>
<td>1318</td>
<td>1313</td>
</tr>
</tbody>
</table>

Table 6 reports the results of the evaluation criteria, for Mobarakeh Steel Company share for two ways.

Table 6. Comparing performance measures of EEMD-ARIMA and ARIMA for Mobarakeh Steel Company share.

<table>
<thead>
<tr>
<th>Shares (stocks)</th>
<th>Prediction Method</th>
<th>Evaluation Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobarakeh Steel Company</td>
<td>EEMD-ARIMA</td>
<td>RMSE</td>
</tr>
<tr>
<td></td>
<td>ARIMA</td>
<td>MAPE</td>
</tr>
</tbody>
</table>

According to Table 6, the RMSE and MAPE model proposed in this study is lower than that of for ARIMA model, and this indicates that the proposed model is far more efficient compared to ARIMA. As mentioned earlier, one of the objectives of this study is to evaluate accurately to predict the combination of EEMD and ARIMA, which in this study, according to the criteria of symmetry (DS), the proposed model, predict the stock price of steel Mobarakeh, predicted with 74% accuracy, and ARIMA method has predicted with 68% accuracy. So hybrid model (EEMD-ARIMA), is more efficient than ARIMA model in terms of accuracy and prediction direction.

Conclusions

In this study, using hybrid model EEMD and ARIMA, it was provided a more accurate prediction model for stock prices. Data and time period of this study include Mobarakeh Steel company weekly prices, from July 2011 to August 2016 (267 observations) in which, 247 first observations are used for sizing up the model, and 20 next observations are used for comparing the performance of prediction accuracy. The results showed that the RMSE and MAPE criteria in the proposed model, has fewer errors and better accuracy than ARIMA model, as well as a measure of symmetry for (DS) in the proposed model, in order to determine the accuracy of forecasts, had higher accuracy. In general it can be said that the use of analytical methods and composition, using time series, can be an appropriate way to predict stock price. In the end, it is recommended that researchers would predict the stock price using other analysis methods, such as wavelet or machine learning methods and compare it with the proposed model in this paper to achieve an optimal model in this regard.
Conflict of interest
The authors declare no conflict of interest

References


