Predicting Jordanian's GDP based on ARIMA modeling

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Abstract. Gross Domestic Product (GDP) is the market value of all goods and services that are produced within the country's national borders in a year, Our study aims to estimate and predict Jordanian's GDP using a time series data for the period from 1978 till 2017, the data has been taken from Jordanian's department of statistics, Minitab and Matlab statistical software's are used , we deploy a wavelet transform (WT) model to decomposes the time series data then detecting the fluctuations and outliers values, also an ARIMA (autoregressive integrated moving average) is established, the fitted ARIMA (2, 2, 1) time series model is the best for modeling the Jordanian's GDP according to the recognition rules and stationary test of time series. The results show that the predicted values are within the range of 5%, and the prediction capability of this model is relatively adequate and efficient in modeling the annual GDP for the next 20 years, thus, the prediction accuracy is considered high. It is concluded that Jordanian's GDP is an upward trend for upcoming 20 fiscal years, Furthermore, Jordanian's government has to follow more comprehensive economic policies and should implement key growth-enhancing reforms to strengthen its economy, also it has to stimulate job-creating growth and creates conditions to increase private investment and improve country's competitiveness.

Keywords: prediction, WT, ARIMA, GDP.

1. Introduction

Gross Domestic Product (GDP) is the market value of all goods and services that are produced within the country's national borders in a year. GDP is a measure that is used to evaluate the overall economic performance of a country; it includes all goods and services produced by the economy including personal consumption, government purchases, private inventories, paid in construction

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costs and the foreign trade balance (net exports). The subject of GDP became of high importance among macro economic variables. Data on GDP is regarded as an important indicator for evaluating the national economic development and growth of the entire economy (Ahmad and Harnhirun, 1996).

Most popular definitions of GDP conceptually identical and can be categorized in three ways: First, it is equal to the total expenditures for all final goods and services produced within the country in a specified period of time (a fiscal year). Second, it is equal to the sum of the value added at every phase of production by all the industries in a country, plus taxes minus grants on products in a facial year. Third, it is equal to the sum of the income generated by production in the country in the fiscal year, which is compensation of employees, taxes on production and imports less grants, and profits (Ahmad and Harnhirun, 1996). GDP aggregates the entire economic motion. It is frequently used as the finest measure of how is the performance of the economy. GDP is generally measured in one of three approaches. First, the Expenditure approach, it involves the market value of all domestic expenditures made on final goods and services of the year, including consumption expenditures, investment expenditures, government expenditures, and net exports the domestic purchases of goods and services and net exports. Second, the Production approach, it is involving the summation of all value-added activities at every phase of production by all industries inside the country, plus taxes and product's subsidies of the period. A third is the Income approach, it is the summation of all aspect of the income made by production within the economy as the remuneration of employees, capital income, and gross operating surplus of enterprises i.e. profit, taxes on production and imports less grants of the period (Reijer, 2010)

The aim of this research is to estimate and predict future Jordanian's GDP, using a time series data for the period from 1978 till 2017, this study is supposed to offer a valuable understanding for the Jordanian's expected GDP. Prediction of GDP involves the application of statistical and mathematical models to predict upcoming developments in the economy. It allows reviewing previous economic movements and predicting how current economic changes will amend the patterns of the previous trend, therefore, a more accurate prediction would provide significant help to the government in setting up economic development goals, strategies and policies. Consequently, an accurate GDP prediction presents a leading insight and an understanding of future economics' trend.

The research question addressed in this study: "Is the ARIMA model a significant model for predicting the future GDP values? ", consequently, we need to attain the subsequent objectives:

- To know the Jordanian's GDP trend.

- To select the best ARIMA model that fits the Jordanian's GDP.

- To predict the Jordanian's GDP.

- To develop ARIMA model for predicting future GDP of the Jordanian's economy.

This paper is organized as follows. Section 2 describes the literature review. Section 3 introduces the methodology and framework. Sections 4 describe the data descriptions and analytical results. Finally, Section 5 presents the conclusions.

2. Literature review

2.1 Gross Domestic Product (GDP)

Economic size is measured by its output, the most widely-used measure of economic output is the GDP, it is generally measured using one of three approaches, and these approaches of measuring GDP should result in the same number, with some possible discrepancies caused by usual mathematical and statistical figures rounding. These approaches as follow: First, the Expenditure approach, it involves the domestic purchases of goods and services plus net exports. Second, the Production approach, sometimes called Net Product or Value-added method, it involves the summation of all value-added activities at every phase of production by all industries inside the country, plus taxes and product's subsidies of the period. A third is the Income approach, it is the summation of all aspect of the income made by production within the economy as the remuneration of employees, capital income, and gross operating surplus of enterprises i.e. profit, taxes on production and imports less grants of the period (Ahmad and Harnhirun, 1996).

Predicting GDP is a vital issue if it is able to understand and capture the future developments of the economy, so it is meaningful to review the economic trends and predict the effect of current economic circumstances on the future GDP trend. This can be done through using time series data of GDP, which consists of observations consecutively generated over time. Such data are ordered with respect to the time, which shows the trend related to the time period observed. The trend may be increasing, decreasing, constant or having a cyclical fluctuation an ups and downs pattern the over time. Also, the data may show that the underlying process has periodic fluctuations of constant length, which is seasonal behavior. Therefore, Modeling would capture this underlying process using the observed time series data so that it could be possible to forecast what would likely be realized at a specific point in time in the future. In predicting macroeconomic time series variables like GDP, there are many possible types of models that are used in literature, in our study we will use ARIMA (Litterman, 1986; Stockton and Glassman, 1987).

In predicting a time series data of GDP as a macroeconomic variable, ARIMA model has been proven to be reliable and an accurate model. (Tsay and Tiao, 1985) used ARIMA modeling, they fitted a non-seasonal data by identifying autoregressive and moving average terms with the help of partial autocorrelation and autocorrelation functions (Box and Jenkins, 1970). Also (Topolewski, et al., 1995) deployed automatic methods were developed to identify as well as estimate the parameters of ARIMA model by utilizing time-series data for a single variable. Furthermore (Mait and Chatterjee, 2012) used a similar methodology to model macroeconomic variable like GDP. However, both the studies were limited to only non-seasonal time series and such modeling needs a long time-series data on the macroeconomic variable in question. (Mei, et. al, 2011) constructed a multi-factor dynamic system VAR prediction model of GDP by selecting six main economic indicators, using time series data extracted from the Shanghai region in China, also (Wang and Wang, 2011) deployed ARIMA for predicting the GDP of China based on time series data. They set up an ARIMA model of the GDP of China from 1978 to 2006. They then choose the best ARIMA model based on statistical tests and predict the GDP from 2007 to 2011. The result shows that the error between the actual value and the predicted value is insignificant which shows that the ARIMA model is highly accurate, Additionally (Wei and Yuan, 2010) used ARIMA model for GDP data series from 1952 to 2007 to predict the GDP of the Shanxi province in China, they found that error between the real GDP value and the predicted value is within 5% range.

2.2 Jordanian's economy

Jordan exists in the most volatile regions in the world. Given the country's high exposure to exogenous shocks, it has been affected by the regional conflicts, the fluctuations of commodity prices, and shifts in geopolitical relations which all compound the country's existing vulnerabilities. A combination of rising external and internal pressures challenges Jordan's balance, like a tightrope walker subject to gusts of winds. Over the past decade, Jordan has pursued structural economic reforms in many sectors like education, health, as well as privatization and liberalization.

The Government of Jordan has introduced social protection systems and reformed subsidies, creating the circumstances for public-private partnerships in infrastructure and making tax reforms. However, further progress is needed so that reforms aimed at enhancing the investment climate and ease of doing business can lead to enhance economic growth and increase its GDP. A major challenge facing Jordan remains to strengthen the economy in the context of a challenging external environment. Adverse regional developments, in particular, the Syria and Iraq crises, remain the largest recent shock affecting Jordan. Continued regional uncertainty and reduced external assistance will continue to put pressure on Jordan. Additionally, a High unemployment rate, high dependency on grants and declining remittances from Gulf economies pose a serious challenge. More comprehensive economic policies and the quick implementation of key growth-enhancing reforms are necessary to reduce the country's sensitivity to external shocks and help to strengthen the economy, also creating conditions for increased private investment and improve country's competitiveness will remain crucial for Jordan to stimulate job-creating growth (World Bank, 2018).

As seen in Figure 1 the annual growth of GDP during the period between 1978 -2017, the average growth rate was 7.6%, and it seems that in the last 10 years the growth is declining due to political instability in the surrounding countries, the 2017 growth rate declined to 3.6%.

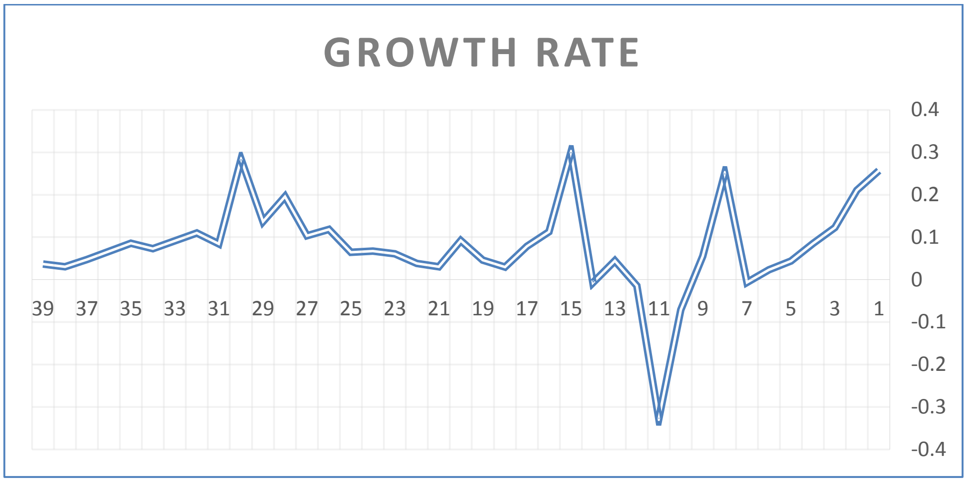

Figure 1: GDP Annual Growth Rate

3. Methodology

This section consists of the research framework, the mathematical model that is used to achieve the purpose of this research and mathematical criteria used is shown in Figure 2.

3.1 Arima model

An Auto regressive (AR) process is a series depends on its lagged values. The AR (p) model is a regression model which defined as appear in equation 1:

$$Yt = \alpha_0 + \alpha_1 Yt - 1 + \alpha_2 Yt - 2 + \ldots + \alpha_p Yt - p. \tag{1}$$

Moving average (MA) model is related if the AR process is not the only mechanism that generates Y, but it contains past values with its error terms. MA (q) process is defined in equation 2:

$$\epsilon t = \beta_1 \epsilon t + \beta_2 \epsilon t - 2 + \beta_3 \epsilon t - 3 + \ldots + \beta q Y \epsilon t - q. \tag{2}$$

Which contains the white noise errors; When Y has both the features of AR and MA, it is called as ARMA (p,q) process. (Gujarathi, et al., 2012) ARIMA

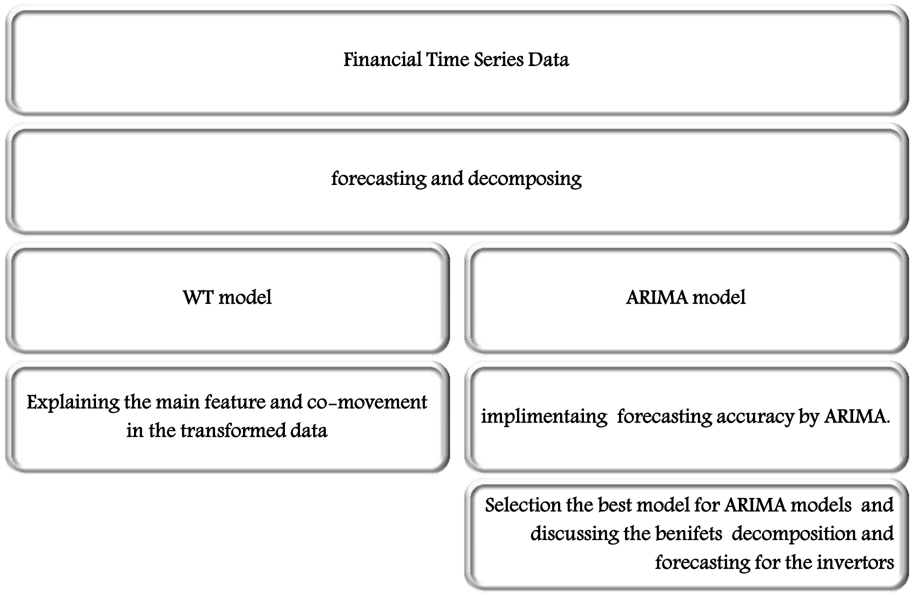

Figure 2: the flowchart of the paper

(Box-Jenkins model) is to classify and estimate a statistical model which can be explained as having generated the sample data. Since the financial time series data are type of non-stationary, therefore differencing the series will yield a stationary time series.

If the financial data becomes stationary when differenced d times, we name the series as I (d). Consequently, if ARMA (p,q) is applied to a series financial data which is I(d), then the original time series is ARIMA(p, d, q). The ARIMA methodology proposed that finding the values of p and q for AR and MA respectively by referring to the correlogram. In MA (q) model, moving average of order q, ACF Dies Down or Cuts off after lag q while for AR (p), autoregressive of order p PACF Dies Down or Cuts off after lag p. (Princeton, 2008). Model diagnosis can be applied based on the values of Root mean Square Error (RMSE) and Mean Absolute percent Error (MAPE).

3.2 Wavelet transform formula

WT is a mathematical model employed to convert the original observations into a time-scale domain. The model is very appropriate with the non-stationary data since most of the financial data are non-stationary. WT can be divided into Discrete Wavelet transform (DWT) and continuous wavelet transforms (CWT). DWT consists of many functions such as Haar, Daubechies, and Maximum overlapping Wavelet transform (MODWT) and others. All of these functions have the same properties with different applications. In this article, the WT will be presented with its equation for all functions. For more details please refer to (Daubechies, 1992; Chiann and Morettin, 1998; Gençay et al., 2002; Al Wadi, 2010)

Wavelets theory is based on Fourier analysis, which represents any function as the sum of the sine and cosine functions. A wavelet is simply a function of time t that obeys a basic rule, known as the wavelet admissibility condition (Gençay et al., 2002):

WT is based on Fourier analysis (FT), which represents any function as the sum of the sine and cosine functions. WT is simply a function of time t that obeys a basic rule, known as the wavelet admissibility condition (Gençay et al., 2002):

$$C_{\varphi} = \int_{0}^{\infty} (\frac{|\varphi f|}{f}) df < \infty, \tag{3}$$

where QF is the Fourier transform and a function of frequency f, of . The WT is a mathematical tool that can be applied to numerous applications, such as image analysis and signal processing. It was introduced to solve problems associated with the Fourier transform, when dealing with non-stationary signals, or signals that are localized in time, space, or frequency.

There are two types of wavelets within a given function/family. Father wavelets describe the smooth and low-frequency parts of a signal, and mother wavelets describe the detailed and high-frequency components. Equation (4) represents the father wavelet and mother wavelet respectively, with j=1,2,3,..., J in the J-level wavelet decomposition (Gençay et al., 2002):

$$\Phi j, k = 2^{-\frac{j}{2}} \phi(t - \frac{2^j k}{2^j}), \tag{4}$$

where J denotes the maximum scale sustainable by the number of data points and the two types of wavelets stated above, namely father wavelets and mother wavelets and satisfies:

$$\int \phi(t) dt = 1, \quad \int \varphi(t) td = 0 \tag{5}$$

time series data, i.e., function f(t), is an input represented by wavelet analysis, and can be built up as a sequence of projections onto father and mother wavelets indexed by both $k, k = 0, 1, 2, ...$ and by $S = 2j, j = 1, 2, 3, ...J$.

Analyzing real discretely sampled data requires creating a lattice for making calculations. Mathematically, it is convenient to use a dyadic expansion, as shown in equation (6). The expansion coefficients are given by the projections:

$$S_{J,K} = \int \phi(t) dt = 1, \;\; d_{J,K} = \int \varphi(t) td = 0. \tag{6}$$

The orthogonal wavelet series approximation to $f(t)$ is defined by:

$$F(t) = \sum S_{J,K}\Phi_{J,K}(t) + \sum d_{J,K}\varphi_{J,K}(t)$$

(7) $$+ \sum d_{J-1,K}\varphi_{J-1,K}(t) + \ldots + \sum d_{1,K}\varphi_{1,K}(t),$$

(8) $$S_J(t) = \sum S_{J,K}\Phi_{J,K}(t),$$

(9) $$D_J(t) = \sum d_{J,K}\Phi_{J,K}(t).$$

The WT is used to calculate the coefficient of the wavelet series approximation in Eq. (6) for a discrete signal, Where S_J (t), and D_J(t) are introducing the smooth and details coefficients respectively. The smooth coefficients dives the most important features of the data set and the details coefficients are used to detect the main features in the dataset. For more details about the WT and its functions please refer to (Al-Khazaleh et al., 2015). When the data pattern is very rough, the wavelet process is repeatedly applied. The aim of preprocessing is to minimize the Root Mean Squared Error (RMSE) between the signal before and after transformation. The noise in the original data can thus be removed. Importantly, the adaptive noise in the training pattern may reduce the risk of over fitting in training phase. Thus, we adopt WT twice for the preprocessing of training data in this study.

3.2.1 Accuracy Criteria

This section consists of two subsections. Firstly, we will present the criteria which have been used to make a fair comparison, and then the framework comparison will be presented with more details. The researchers have been adopted to compare the performance of the models within three types of accuracy criteria which are Mean square error (MSE), Root mean squared error (RMSE) and Mean absolute error (MAE). For more details about the mathematical model refer to (Aggarwal et al., 2008; Wadi et al., 2011).

4. Results

4.1 Data description

In this research, we use a time series data that represent the Jordanian's GDP for the period from 1978 till 2017, the data has been taken from Jordanian's department of statistics. The Matlab and Minitab statistical software were used to analyze the data.

As shown in the Figure 4 a histogram, accumulated histogram and descriptive statistics of the time series show a non-linear path; therefore, it is none stationary homogeneous type, characterized by random changes from one period to another.

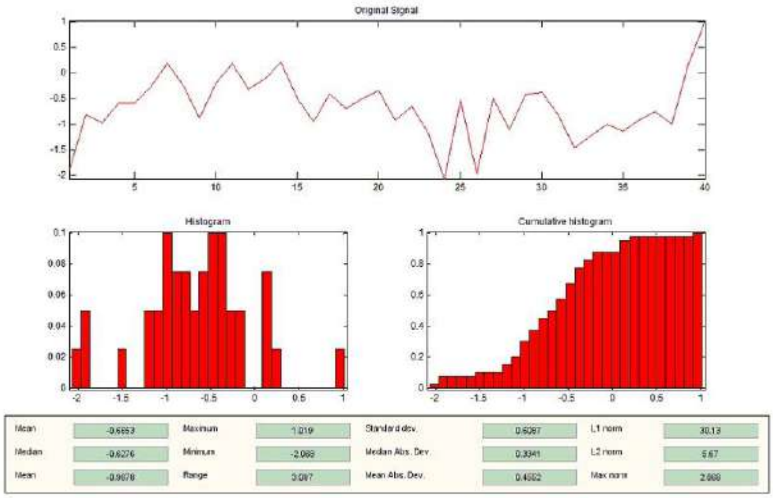

Figure 3: Data analysis matrix

4.1.1 Decomposing time series

A time series generally has three components that are a trend, noise and seasonal components. Decomposition of the time series means separating original time series into these components: First-Trend: The increasing or decreasing values in any time series. Second-Seasonal: The repeating cycle over a specific period in any time series. Third-Noise: The random of values in any time series. Figure 1 shows the decomposition based on WT. Before proceed to make data decomposition the data has been transformed using the log function in second order since the data is highly fluctuated, the decomposition procedure consists of a1, which is the approximated coefficients used for the proper forecasting and d1 which shows the fluctuations of data. Mathematically, the equation can be represented as S= a1+d1 where S is the original data.

Refer to the Figure 5 a visual inspection of the time plots shows that GDP data time series has a trend of random fluctuations, which means that the data are non-stationary and it is not constant around mean and variance. This type of non-stationary time series data contains a seasonal trend can be carried out by spectral analysis function which is WT. which lead to transform a random trend into a linear trend. Since d1 explains the main features and fluctuations of the time series data, it has been clear that there were many fluctuations that the Jordanian's economy faced during the study period.

After we have done the decomposing process of time series data, we applied the ARIMA forecasting process.

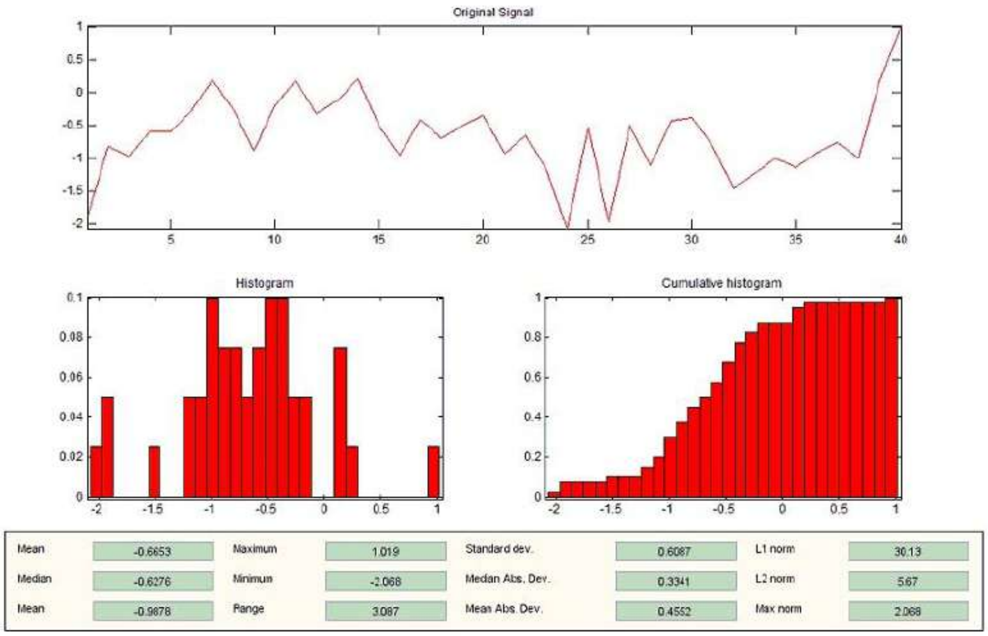

Figure 4: Data Description of GDP

After we have done the decomposing process of time series data, we applied the ARIMA forecasting process.

Table 1: ARIMA Model for Jordanian's GDP

	Fitted ARIMA Model
Model	(2,2,1)
MASE	0.3708
RMSE	0.0380

The fitted ARIMA models were diagnosed using MASE and RMSE. Parameter estimation for the ARIMA models was done using the Gaussian MLE criterion. The ARIMA models fitted based on the lowest value of MASE (0.3708) and RMSE (0.0380) as appear in Table 2, with a fit ARIMA is ARIMA (2,2,1). Where yt represents the value of GDP.

Figures 6 and 7 show the GDP original and predicted values, the data series-stationary from (1978 till 2017) and the forecasted values of GDP for the coming twenty years (years 2017 till 2036), this suggests that the GDP long term trend is

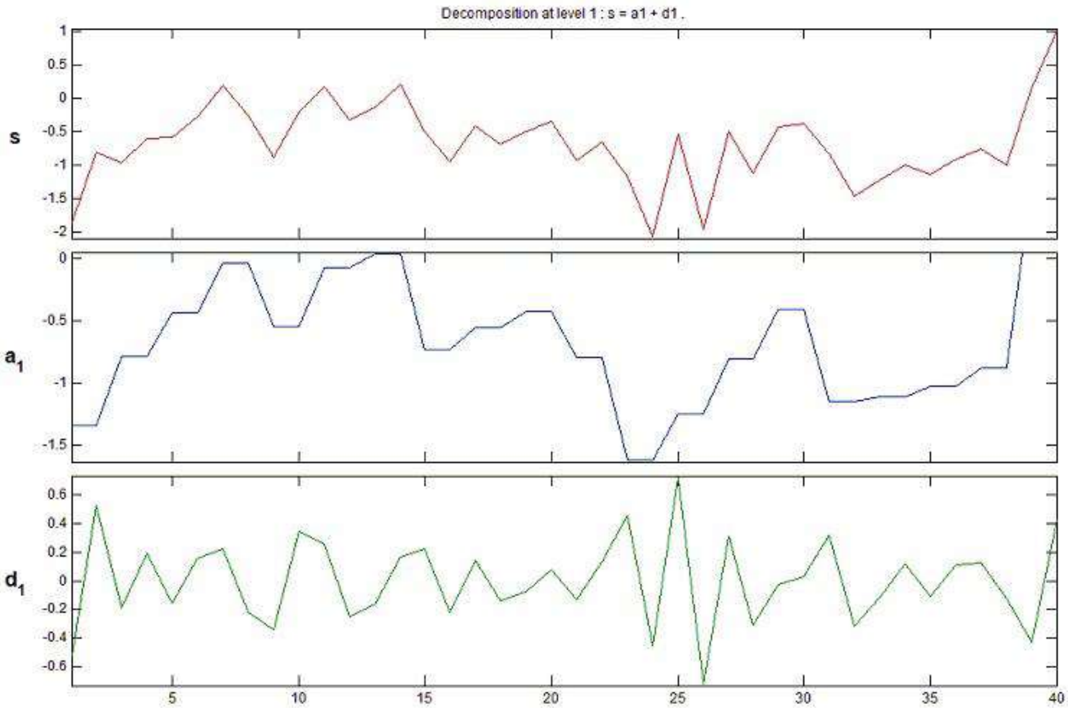

Figure 5: WT decomposition

up ward slopping, which gives an indication that Jordanian's economy long-term view considered positive and will continue its growing.

5. Conclusion

In this paper we deployed a WT model to decompose the data to detect the fluctuation and outlier values, then we utilized ARIMA model in predicting Jordanian's GDP, using GDP time series of the years 1978 to 2017. It is clear that the ARIMA model offers an excellent technique to predict any single data variable like GDP as an important macroeconomic indicator. It is strength lies in its fitting varieties of different types of time series with any pattern. In the process of model building, the original data is found a non- stationary then transformed to be stationary. An ARIMA (2,2,1) model is developed for analyzing and predict GDP among all of various tentative ARIMA models as it has the lowest BIC values. From the results, it can be observed that influence R Square value is (95%) high and Mean Absolute Percentage Error is very small for the fitted model. Therefore, the prediction accuracy is high. It is concluded that Jordanian's GDP will continue growing in the same growth pattern in

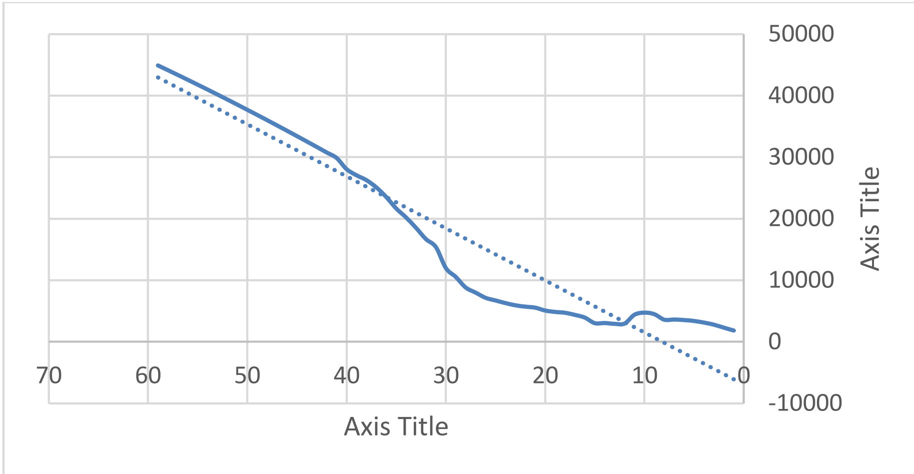

Figure 6: GDP, Billions of JD

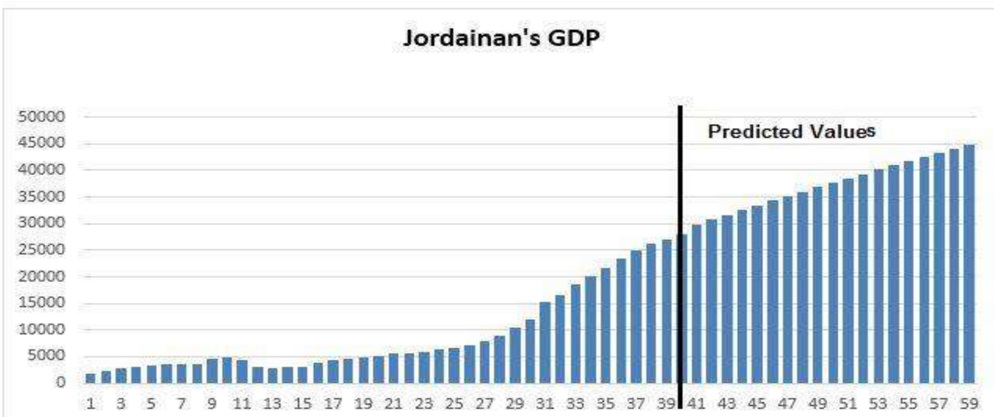

Figure 7: jordanians GDP prediction

the coming 20 years, Jordanian's government has to follow more comprehensive economic policies and implement key growth-enhancing reforms to strengthen the economy, also it has to stimulate job-creating growth and creates conditions to increase private investment and improve country's competitiveness.

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