PRZESTRZEŃ Społeczna Social SPACE
Volume 22 Issue 01
2022

Revenue's Forecasting of Aqaba Ports Company Using Wavelet Transform and ARIMA Models

S. AL wadi*

Department of Finance, Faculty of Business, the University of Jordan, Jordan
E-mail: sadam_alwadi@yahoo.co.uk

Osama Mohammad Al-Rawashdeh

Department of Hotel Management & Tourism Science, Al-Balqa Applied University, Aqaba University College, E-Mail: osama.rawashdeh@bau.edu.jo

Omar ALsinglawi

Department of accounting, the University of Jordan/ Jordan,
E-mail: o.alsinglawi@ju.edu.jo

Bara'ah A. ABU Dalwein

Master degree student, Aqaba Company for Ports Operation & Management /Jordan. E-mail: ba.abu-dalween@acpom.com.jo

Mohammad H. Saleh

Department of Finance, Faculty of Business, the University of Jordan, Jordan,
E-mail: mohsaleh1966@yahoo.com

Jamil J. jaber

Department of Finance, Faculty of Business, the University of Jordan, Jordan,
E-mail: j.jaber@ju.edu.jo

Firas Al-Rawashdeh

Department of Finance, Faculty of Business, the University of Jordan, Jordan,
E-mail: f_rawashdeh@ju.edu.jo

Abstract

This study aims to increase revenue forecasting accuracy by modeling a time series of monthly revenue data obtained from Aqaba Company for Ports Operations and Managements - Jordan from January 2011 to December 2020. Numerous mathematical functions are utilized in this investigation, including the non-linear spectral model, the maximal overlapping discrete wavelet transform (MODWT) based on the Coiflet function (C4), and the autoregressive integrated moving average (ARIMA). Significant findings of this work include an explanation of all previous events within the specified period and the development of a new forecasting model by merging the best MODWT function (C4) with the fitted ARIMA model. In addition, this study indicates how MODWT may dissect financial data, highlighting the most volatile events and enhancing the accuracy of forecasts. Root Mean Square Error (RMSE) will be utilized to assess forecasting ability. To make the empirical findings helpful to Aqaba Ports Company, we predict the results for the following five years. Modeling the data using the Maximum Overlapping Discrete Wavelet Transform (MODWT) based Coiflet function (C6) (ARIMA-MODWT (C6) with fitting ARIMA (2,1,2)). Therefore, all previous occurrences and fluctuations throughout the specified time frame will be described and explored in detail. MODWT-ARIMA (C6) is the best model compared to Haar, Daubechies (D4), Coiflet (C4), Least Symmetric (LA8), and Best Localized (Bl14) with fitted ARIMA model based on RMSE statistical criterion. This study highlights the deconstruction capability of MODWT by highlighting major events, fluctuations, and forecasts. The future values till the end of 2025 were then predicted.

Keywords: MODWT's Functions, Revenue, ARIMA Model, Forecasting.
Mathematical code classification: 62M15, 49M27, 62M20, 42C40.

1. Introduction and Literature Review

Any country's development and economic growth depend on the performance metrics of its international trade and investments because no single country can exist on its own (Osadume, 2020). Domestic and international trades will always require an efficient transportation system to transport marketable goods. The maritime business presents an opportunity to transport large volumes of cargo. Considering that more than 80% of the volume of international trade is transported by sea, countries with coastal features need to have port operations (Al Hayek, 2018; Munim & Schramm, 2018).

The port of Aqaba began its activity in 1939. In 1952, the port of Aqaba was established by a royal will, after which several legal changes included tasks and titles, such as the Maritime Corporation and the Aqaba Port Department, until the year 1979 was issued when the Jordanian Royal Decree was issued, merging the Naval Corporation and the Aqaba Port Department under The name of the Ports

Corporation. In 2017, the Council of Ministers decided to approve the transformation of the Ports Corporation into a limited joint-stock company wholly owned by the government under the name Aqaba Company for Ports Operation & Management (ACPOM) (http://www.aqabaports.com.jo).

Ports play a crucial role in economic growth, as they are seen as a major development engine for the national economy, a central link in integrating the transport system, and one of the fundamentals of development due to the impact of their services on the national economy as a whole (Nam & Song, 2011). The corporation is responsible for the management, operation, and repair of the operational assets of the seaports. This is one of the most important responsibilities of the port of Aqaba. Providing ships with essential dockside services. The yards and logistical regions are operational and operational within the Aqaba Special Economic Zone. Development of operational processes and optimal utilization of the port's resources and assets (Wang et al., 2021). The port's distinguished geographical location links Africa with the Middle East and West Asian countries and is the link between the Far East, India, and the countries of the Middle East without the need to pass through the Suez Canal (https://en.wikipedia.org).

The port of Aqaba experienced high productivity rates for various goods and cargo types, based on international standards. The port of Aqaba can accommodate ships of various sizes and types and ships anchored at the berth, and the largest size of ships that can be accommodated is approximately 406,000 tons of liquid materials and approximately 74,000 tons for other ships (Michaelides et al., 2019).

2. Revenue Forecasting:

The importance of revenue forecasting lies in the fact that it illuminates the current and future state of the firm. It aids in better planning and decision-making, allowing the organization to reach new heights without the management feeling overwhelmed. The best aspect is that forecasts are based on precise data and actionable insights, transforming the future financial performance from a wish list into a feasible business strategy. The revenue is the money a business anticipates receiving from its operations (Comeau et al., 2019; Miles et al., 1997).

It is crucial to distinguish between revenue and sales. While sales is the number of contracts signed and money eventually received, revenue is the actual amount you bring in each period.

For revenue forecasting, far too many business owners mistake sales for revenue, which is not the case. The most accurate form of forecasting is concentrating on the exact quantity of money brought into the organization during a given period, rather than the promissory notes collected later.

Revenue forecasting is an in-depth review of past performance that enables you to estimate your company's potential year revenue. Forecasting future revenue is a crucial component of any business plan since it helps determine how much and how rapidly the firm will expand (Cohen et al., 1997). We should consider revenue forecasting in the following three principles: analysis, management, and strategy. As a result, numerous publications on revenues have been written, including Cavusgil (1985); Kiani and Pourfakhraei (2010), which examined the Non-linear processes of accurate modeling by statistical models. Comparing the application of ANFIS as a non-linear fuzzy neural network model with ARIMA as a linear model for forecasting the export revenues of Iran's agricultural exports. As an empirical application, the forecasting performance of the models was compared for 1, 2, and 4 years into the future using standard forecast performance measures. In terms of error measurements such as RMSE and MAD, the ANFIS non-linear model forecasts were significantly more accurate than the linear classical ARIMA model employed as a benchmark (Fildes & Goodwin, 2007).

In contrast, based on the R 2 criterion, the ANFIS non-linear model was superior to the ARIMA linear model. Using forecast assessment criteria, it has been proved that the ANFIS non-linear model beats the ARIMA model. Therefore, the ANFIS model is an excellent method for improving the accuracy of export income forecasts for Iran's agricultural products. Using tax revenue data and BVAR models, another study Tanzi (1989) decomposes Swedish corporate tax revenues and ties the tax base to the macroeconomy and other pertinent variables. In addition, they use the popular wisdom that tax revenues are fundamentally random walks but emphasize that a breakdown of the tax base may be related to the macroeconomy and other literature-based causes.

The BVAR models assess the significance of various shocks on earnings and the tax base and anticipate corporate tax revenues. The empirical findings indicate that external, macroeconomic, and financial shocks explain a substantial portion of the variance in forecasting error for corporate profits. In contrast, shocks in profits, tax adjustments, and fiscal measures explain a substantial portion of the variance in forecasting error for the corporate tax base. Our findings may have far-reaching implications for comprehending how various factors influence business earnings and, by extension, corporation tax collections. This is particularly significant since companies can choose when, how, and in what manner to declare profits based on tax deductions, transfer pricing, group contributions, and other specific arrangements.

Moreover, Rausser et al. (2018) demonstrated the efficacy of three distinct time series models, the accurate outcomes of forecasting, and overall tax income between 2016 and 2017, laying the groundwork for the government of Pakistan to formulate sound policies. The findings of this study indicate that, among these models, the ARIM. A model provides more accurate forecasts for Pakistan's overall tax collections. In addition, Jafar et al. (2013) created planning the operations of customs authorities and estimated the state budget revenues from customs payments. The significance of this stage is in the requirement to predict with a certain degree of probability the future condition of the customs system's separate components and, as a result, prepare the necessary management actions to mitigate the negative effects. We were able to detect the impact of the COVID-19 pandemic on the Ukrainian economy, which ultimately resulted in an internal financial and economic crisis, by analyzing the findings of factor analysis by measuring the key components of chosen monetary and macroeconomic parameters (Martyniuk et al., 2021). From September 2019 to January 2020, it was determined that the macroeconomic component was developing slowly, which was represented in a steady increase in GDP, exports, and imports, with low inflation.

In contrast to this tendency, the monetary element, which has a greater impact on the national economy, is dropping steadily. From February to September of 2020, the most precipitous fall was noticed. This, coupled with a bad political trend within Ukraine and negative external variables resulting from the COVID-19 epidemic, has resulted in severe economic effects for Ukraine.

As a result of a thorough literature review and extensive research, the authors were unable to locate any articles that used the MODWT functions (Haar, Daubechies (d4), Coiflet (c4), Least Symmetric (LA8), and Best Localized (Bl14) in conjunction with ARIMA to analyze revenue data, and then compared these results to those obtained from a directly fitted ARIMA model. Therefore, there is still potential for improvement in this research.

This work is structured as follows: the introduction and literature review comes first, followed by the presentation of the mathematical model. The Research Design and Methodology will be detailed in the third section. The results and discussion will be presented in section 4, followed by the conclusion, limitation, and future study.

3. Mathematical models

This section gives a background of the main concepts used in our study:

Wavelet Transform (WT)

WT is a mathematical function used to convert the original time series data into a time-scale domain. This model is very attractive with the non-stationary data, especially stock market data. WT is divided into Discrete Wavelet transform (DWT), continuous wavelet transforms (CWT), and MODWT. These functions have the same aspects in general. The main difference between DWT and MODWT is that DWT can be used for a specified number of data (number of observations should be 2 of power J), while MODWT can be used for any data size. Therefore, this article will focus on MODWT since it is more flexible and modern (Gençay et al., 2001). WT is an extension of Fourier transform (FT) based on sine and cosine functions. WT satisfies the admissibility condition (Funke et al., 2005):

$$C_{\varphi} = \int_{0}^{\infty} \varphi(f) \vee \frac{\varphi(t)}{f} df < \infty \tag{1}$$

Where $\varphi(f)$ are the FT and a function of frequency f, $\varphi(t)$. The WT is used in many image analysis and signal processing applications. It was introduced to overcome the problem of FT, especially when dealing with time, space, or frequency (Demiralp et al., 1999).

There are two types of WT which are Father wavelet describes the low-frequency parts (smooth coefficients), and the mother wavelet describes the high-frequency (detailed coefficients) components as shown in equation (2) respectively, with j=1,2,3,..., J in the J-level wavelet decomposition:

$$\phi j,k = 2^{\left(\frac{-j}{2}\right)} \phi\left(t - \frac{2^j k}{2^j}\right)$$
$$\varphi j,k = 2^{\left(\frac{-j}{2}\right)} \varphi\left(t - \frac{2^j k}{2^j}\right) \quad (2)$$

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:

$$\int \phi(t)dt = 1 \wedge \int \varphi(t)dt = 0 \quad (3)$$

The WT is used to calculate the approximation and details coefficients, respectively. The smooth coefficients contain the most important features of the original data, while the details coefficients are used to detect the major fluctuations of the original data. Generally, WT has popular transform functions Gençay et al. (2001), namely Haar, Daubechies(d4), coiflet (c6, Least Asymmetric (LA8), and best-localized (bl14). The number of main properties of these functions follows. WT functions are arbitrary regular except in the Haar model. Interestingly, WT functions do not have explicit expression except in the Haar model. WT functions use real numbers. WT functions are orthogonal and compact support, an arbitrary number of zero moments, existing of the scale function, orthogonal analysis, bio-orthogonal analysis, continuous/discrete transformation, exact reconstruction, and fast algorithm.

Autoregressive Integrated Moving Average Model (ARIMA):

The auto-regressive moving average (ARMA) models are used in time series analysis to describe stationary time series. The ARMA model combines a moving average (MA) model and an autoregressive (AR) model. A time-series $\{e_t\}$ is called a white noise (WN) process, $\{Y_t\}$ is called Gaussian process iff for all t, e_t is iid $N(0, \sigma^2)$. A time-series $\{Y_t\}$ is said to follow the ARMA(p,q) model if (Jaber et al., 2020; Silva et al., 2021):

$$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} \dots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} \dots - \theta_q e_{t-q} \quad (4)$$

Where q and p are non-negative integers, p represents an order of the autoregressive part (AR), q is defined as the order of the first moving part (MA), and $\{e_t\}$ is the white noise (WN) process. An extension of the ordinary ARMA model is the auto-regressive integrated moving-average model (ARIMA(p,d,q)) given by Jaber et al. (2020).

$$\phi_p(B)(1-B)^d Y_t = \theta_0 + \theta_q(B) e_t \quad (5)$$

Where p, d, and q denote orders of auto-regression, integration (differencing), and moving average, respectively.Whend=0, the ARIMA model reduces to the ordinary ARMA model.

Accuracy Criteria

Root Means Squared Error (RMSE) is the most popular statistical criterion used in forecasting. It measures the average error performed by the model in predicting the outcome of an observation. It is defined as the square root of the mean square error as $\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{\sum_{i=1}^{N}(\text{actual value}-\text{predicted value})^2}{N}}$ Where N represents the number of observations. (Aptula et al., 2005; Jaber et al., 2020; Shawer & Al-Ajlouni, 2018).

4. Research Design and Methodology

The objectives of this research are as follows:

Firstly, modeling the revenue data using WT's functions.

Secondly, discuss the fluctuations during the historical data.

Finally, improving the forecasting accuracy by combining MODWT's functions with the ARIMA model to introduce a new method called MODWT-ARIMA (C6). The following follow chart explores the methodology with all its elements.

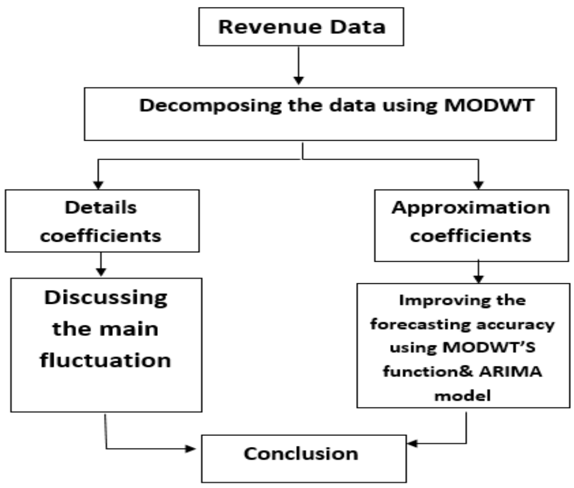

Figure 1. Research Flowchart

Our methods for handling our data can be described in greater depth: First, revenue data are modeled using WT's function. Second, we decompose the given historical return data using the MODWT functions (Haar, Daubechies (d4), coiflet (c4), least symmetric (LA8), and best localized (Bl14)). Thirdly, we employ the detail coefficients to identify fluctuations and examine historical data. Fourth, we utilize an ARIMA model with fitted approximation coefficients for predicting. Finally, a comparison is made between the novel method and a pure ARIMA direct model.

The suggested method's mechanism is summed up as the MODWT conversion of the data into two sets: the details series (DA1 (n)) and the approximation series (CA1 (n)). These two series exhibit good behavior for the data set, particularly the financial data, which has varied dramatically. The altered data can then be anticipated with greater precision. The good behavior of these two series is a result of the filtering effect of the MODWT. In addition, we have utilized the approximation series because it functions as the primary component of the transform. The wavelet technique is frequently applied when the data pattern is extremely jagged. Pre-processing reduces statistical criteria, such as Root Mean Squared Error (RMSE), between the signal before and after transformation. Thus, the noise in the original data may be eliminated. Significantly, the adaptive noise in the training pattern may lower the likelihood of overfitting during the training phase. In this study, we employ MODWT twice to pre-process training data. The following diagram explains the modification method's procedure.

To conduct a fair comparison, we apply 90 percent of the dataset (original and modified data) to the suggested model and then select the best model. Then, for the remaining data, apply the best model and the other proposed models (10 percent). In this step, we can confirm that our new model is specifically superior to the others. Typically, researchers divide their data 80/20. Nevertheless, given that we have vast data a 90/10 split is sufficient. Then, the future values for the next 60 months (observations) will be projected so that the results are relevant and worthy.

5. Empirical Results

In this section, we present the data used in our study. Then we give the numerical results obtained when applying our models to the considered dataset.

5.2. Results and Discussion

The current study examines the revenue time series data collected from Aqaba Ports for Operations & Managements /Jordan from January 2011 to December 2020, with the number of observations being 120. Then the fluctuations during the selected period will be drawn and discussed in the next figure.

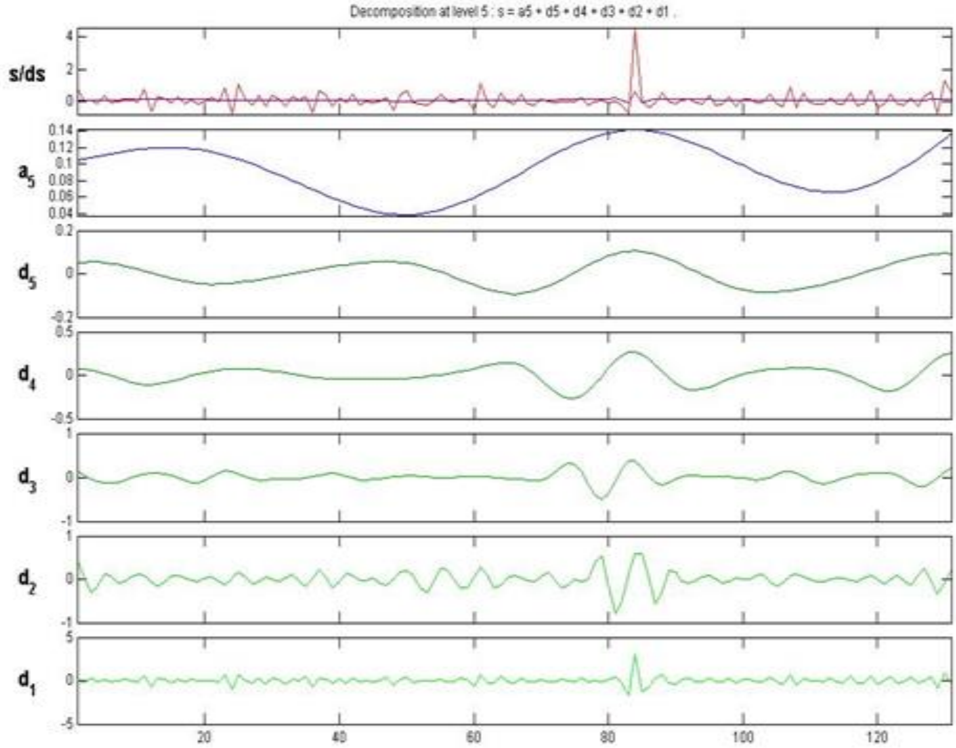

Figure.2 Decomposing the data using MODWT

Figure 1 depicts the dissection of the dataset containing C6 function data from the MODWT model. This method is appropriate for revealing the variations, magnitudes, and phases of the dataset's revenue data. MODWT (C6) to historical data decomposes them into many resolution levels that reveal their core structure and generates detail coefficients at every single decomposition level. According to the MODWT mechanism, the WT can calculate decomposition levels using the following equation: S= a1+d1+d2+d3+d4+d5, where S represents the source signal. The following section consists of one approximation level (a1), which displays the plot of the approximation coefficients for the modified data used in further forecasting procedures, as this section contains the primary characteristics of the dataset.

The subsequent portions of d1 through d5 reflect the level of the details, and since d1+d2+d3+d4+d5 is the plot of the details coefficients, this level can be utilized to explain the fluctuation. In general, coefficients at any level of detail can be utilized to explain or detect the major changes. Consequently, based on d1 (level 1 of details coefficients), which can be used for detections, it is evident that the behavior of the data is stationary from observation 1 to observation 80, indicating that no significant events have occurred from 2011 to 2017 and that the revenues are almost identical. These outlier statistics result from the Syrian civil conflict, as the port of Aqaba has been utilized rather than other ports. As a result, the port of Aqaba has increased its revenue. After then, the numbers remain steady until the end, indicating no substantial fluctuations in revenue. These high levels of variability force researchers to concentrate on predicting the next values. In this article, MODWT with the C4 function and fitted ARIMA models will be integrated to improve predicting accuracy, as this is a highly important issue for researchers. Consequently, the fitted ARIMA model must be approximated. To generate a statistically meaningful level of predictions, we divide the data into two groups, with group one containing 90% of the observations and group two containing 10% of the observations.

First, we proceed with the forecasting for the first group using MODWT functions (Haar, Daubechies (d4), Coiflet (c4), Least Symmetric (LA8), and Best Localized (Bl14)) combined with ARIMA models to obtain predicted values. We compare the original values with the predicted values for all MODWT functions based on the statistical criteria, which is RMSE, and then we will confirm our results by proceeding with the forecasting for the second group; therefore, Table 2 displays the findings obtained by the suggested models for the first 90% and 10% of the utilized data set. Note that the ARIMA - direct model is the result of applying the pure ARIMA model directly to the original data. The suggested models denoted by ARIMA-MODWT (Haar), ARIMA-MODWT (d4), ARIMA-MODWT (LA8), ARIMA-MODWT

(Bl14), and ARIMA-MODWT (C6) will be applied to the data set, and the fit ARIMA (0,1,1) will be used to make a statistically significant evaluation of the entire collection of models. Based on the value of RMSE, ARIMA-MODWT (C6) is the best model since it has the lowest value of RMSE, 0. 1201493 with fit ARIMA(2,1,2), followed by ARIMA-MODWT (Bl14) with RMSE= 0.1368335 with fit ARIMA (1,1,0) and ARIMA-MODWT (Haar) with RMSE= 0.251215 with fit ARIMA (1,1,0). (5,1,2). The subsequent model will be ARIMA-MODWT (LA8) with RMSE=0.1721971 and fit ARIMA(0,1,3), while ARIMA-MODWT (d4) has RMSE= 0.2217772 and fit ARIMA(1,1,0), and the ARIMA model directly has the highest RMSE value of RMSE =0.5003174, indicating that this model is inconvenient for forecasting processing.

Table 4 MODWT- ARIMA models for 90% and 10% of observations

Sample %	**GARCH- MODWT models**	**ARIMA(p, d,q)**	**RMSE**
90% of observations	Haar	(1,1,0)	0.251215
	d4	(1,1,0)	0.2217772
	la8	(0,1,3)	0.1721971
	bl14	(5,1,2)	0.1368335
	c6	**(2,1,2)**	**0.1201493**
	ARIMA-direct	(0,1,1)	0.5003174
10% of observations	Haar	(1,1,0)	0.595211838
	d4	(1,1,0)	0.624430843
	la8	(0,1,3)	0.565983839
	bl14	(5,1,2)	0.595753597
	c6	**(2,1,2)**	**0.500074328**
	ARIMA-direct	(0,1,1)	0.500317367

Finally, the future values will be predicted for 60 months (observations). Note that the growth of return will be predicted at a confidence interval of 95% to show how much the growth during the next years using the best model, ARIMA-MODWT (C6) with fit ARIMA (2,1,2). Therefore, the next table will show the results with its figure. Therefore, the predicted values for the years between 2022 into 2025 will be presented in the next table.

Table 2. shows the predicted values until the year 2025

year	Month	growth of return	Lo 95	Hi 95
2022	January	0.0864553	-0.52667	0.699576
	February	0.086447941	-0.52667	0.699569
	March	0.08644074	-0.52668	0.699562
	April	0.086433692	-0.52669	0.699555
	May	0.086426506	-0.52669	0.699547
	June	0.08641935	-0.5267	0.69954
	July	0.086412221	-0.52671	0.699533
	August	0.086405067	-0.52672	0.699526
	September	0.086397919	-0.52672	0.699519
	October	0.086390775	-0.52673	0.699512
	November	0.086383627	-0.52674	0.699505
	December	0.08637648	-0.52674	0.699497
year	**Month**	**growth of return**	**Lo 95**	**Hi 95**
2023	January	0.086369334	-0.52675	0.69949
	February	0.086362187	-0.52676	0.699483
	March	0.086355041	-0.52677	0.699476
	April	0.086347894	-0.52677	0.699469
	May	0.086340747	-0.52678	0.699462
	June	0.0863336	-0.52679	0.699455
	July	0.086326454	-0.52679	0.699447
	August	0.086319307	-0.5268	0.69944
	September	0.08631216	-0.52681	0.699433
	October	0.086305014	-0.52682	0.699426
	November	0.086297867	-0.52682	0.699419
	December	0.08629072	-0.52683	0.699412
2024	January	0.086283573	-0.52684	0.699405
	February	0.086276427	-0.52684	0.699397
	March	0.08626928	-0.52685	0.69939
	April	0.086262133	-0.52686	0.699383
	May	0.086254987	-0.52687	0.699376
	June	0.08624784	-0.52687	0.699369
	July	0.086240693	-0.52688	0.699362
	August	0.086233546	-0.52689	0.699355
	September	0.0862264	-0.52689	0.699347
	October	0.086219253	-0.5269	0.69934

	November	0.086212106	-0.52691	0.699333
	December	0.08620496	-0.52692	0.699326
2025	January	0.086197813	-0.52692	0.699319
	February	0.086190666	-0.52693	0.699312
	March	0.086183519	-0.52694	0.699304
	April	0.086176373	-0.52694	0.699297
	May	0.086169226	-0.52695	0.69929
	June	0.086162079	-0.52696	0.699283
	July	0.086154933	-0.52697	0.699276
	August	0.086147786	-0.52697	0.699269
	September	0.086140639	-0.52698	0.699262
	October	0.086133492	-0.52699	0.699254
	November	0.086126346	-0.52699	0.699247
	December	0.086119199	-0.527	0.69924

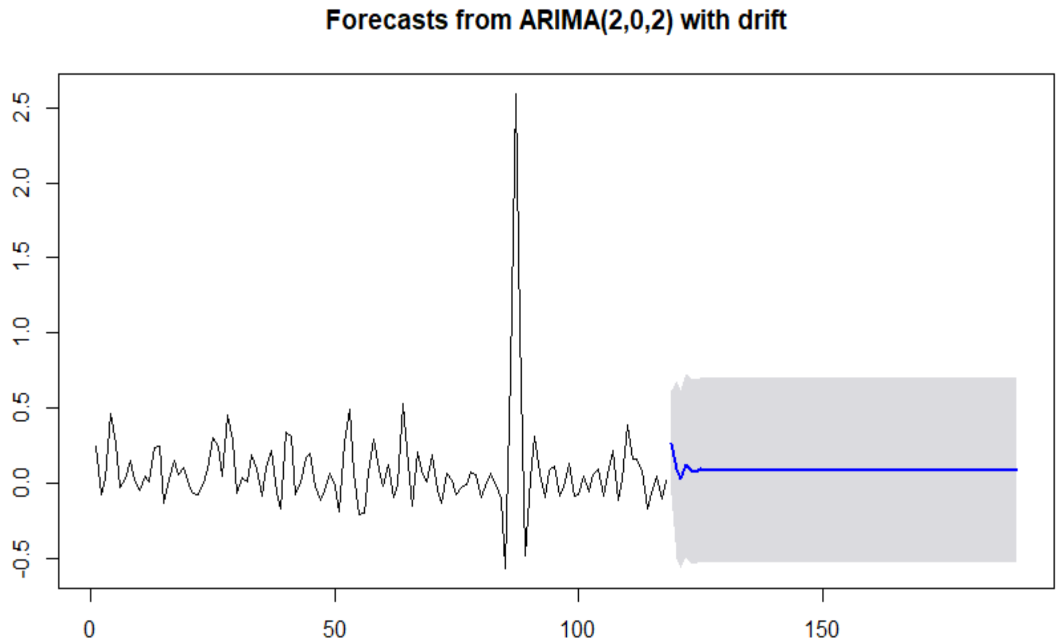

Fig.3 shows the predicted value using ARIMA-MODWT (C6) with fit ARIMA (2,1,2)

Based on Fig.3, it is noticeable that the revenues of the Aqaba ports company are stationary and regular until the end of the year 2025 if there are no external factors effects such as COVID-19 using ARIMA-MODWT (C6) with fit ARIMA (2,1,2) function.

6. Conclusion

This article discusses revenue data collected from Aqaba Ports Company for Operations & Managements/Jordan from January 2011 to December 2020, with 120 observations. These data were modeled using Maximum overlapping Discrete Wavelet Transform (MODWT)-based Coiflet function (C6) (ARIMA-MODWT (C6) with fit ARIMA (2,1,2)). Therefore, historical occurrences and fluctuations throughout the specified time frame will be described and explored in detail. In addition, a new model, MODWT- ARIMA (C6), is modified; this model is superior to other suggested models (Haar, Daubechies (d4), Coiflet (c4), Least Symmetric (LA8), and Best Localized (Bl14)) with fitted ARIMA model based on statistical criteria, RMSE. This article demonstrates the ability of MODWT in decomposition, highlighting significant events, fluctuations, and forecasting. Then, the future values were anticipated through the end of the year 2025.

7. Limitations and future work

This study utilized a single type of data, namely revenue data collected from Aqaba Company for Ports Operations & Managements/Jordan. Consequently, this approach can be generalized to various forms of data and applied to any massive data.

References

Al Hayek, M. A. (2018). The relationship between sales revenue and net profit with net cash flows from operating activities in Jordanian industrial joint stock companies. *International Journal of Academic Research in Accounting, Finance and Management Sciences, 8*(3), 149-162. https://doi.org/10.6007/IJARAFMS/v8-i3/4757

Aptula, A. O., Jeliazkova, N. G., Schultz, T. W., & Cronin, M. T. D. (2005). The better predictive model: high q2 for the training set or low root mean square error of prediction for the test set? *Qsar & Combinatorial Science, 24*(3), 385-396. https://doi.org/10.1002/qsar.200430909

Cavusgil, S. T. (1985). Guidelines for export market research. *Business Horizons, 28*(6), 27-33. https://doi.org/10.1016/0007-6813(85)90082-5

Cohen, M. A., Eliashberg, J., & Ho, T. H. (1997). An anatomy of a decision-support system for developing and launching line extensions. *Journal of Marketing Research, 34*(1), 117-129. https://doi.org/10.1177/002224379703400110

Comeau, S., Cornwall, C. E., DeCarlo, T. M., Doo, S. S., Carpenter, R. C., & McCulloch, M. T. (2019). Resistance to ocean acidification in coral reef taxa is not gained by acclimatization. *Nature Climate Change, 9*(6), 477-483. https://doi.org/10.1038/s41558-019-0486-9

Demiralp, T., Ademoglu, A., Schürmann, M., Basar-Eroglu, C., & Basar, E. (1999). Detection of P300 waves in single trials by the wavelet transform (WT). *Brain and language, 66*(1), 108-128. https://doi.org/10.1006/brln.1998.2027

Fildes, R., & Goodwin, P. (2007). Against your better judgment? How organizations can improve their use of management judgment in forecasting. *Interfaces, 37*(6), 570-576. https://doi.org/10.1287/inte.1070.0309

Funke, H., Scheinost, A. C., & Chukalina, M. (2005). Wavelet analysis of extended x-ray absorption fine structure data. *Physical Review B, 71*(9), 094110. https://doi.org/10.1103/PhysRevB.71.094110

Gençay, R., Selçuk, F., & Whitcher, B. (2001). Differentiating intraday seasonalities through wavelet multi-scaling. *Physica A: Statistical Mechanics and its Applications, 289*(3-4), 543-556. https://doi.org/10.1016/S0378-4371(00)00463-5

Jaber, J. J., Ismail, N., Ramli, S., Al Wadi, S., & Boughaci, D. (2020). Assessment OF credit losses based ON arima-wavelet method. *Journal of Theoretical and Applied Information Technology, 98*(09), 1379-1392. http://www.jatit.org/volumes/Vol98No9/5Vol98No9.pdf

Jafar, T. H., Haaland, B. A., Rahman, A., Razzak, J. A., Bilger, M., Naghavi, M., . . . Hyder, A. A. (2013). Non-communicable diseases and injuries in Pakistan: strategic priorities. *The Lancet, 381*(9885), 2281-2290. https://doi.org/10.1016/S0140-6736(13)60646-7

Kiani, B., & Pourfakhraei, M. A. (2010). A system dynamic model for production and consumption policy in Iran oil and gas sector. *Energy Policy, 38*(12), 7764-7774. https://doi.org/10.1016/j.enpol.2010.08.036

Martyniuk, V., Wołowiec, T., & Mieszajkina, E. (2021). Planning and Forecasting Customs Revenues to the State Budget: A Case Study of Ukraine. *European Research Studies, 24*(1), 648-665. https://doi.org/10.35808/ersj/2301

Michaelides, M. P., Herodotou, H., Lind, M., & Watson, R. T. (2019). Port-2-port communication enhancing short sea shipping performance: The case study of Cyprus and the Eastern Mediterranean. *Sustainability, 11*(7), 1912. https://doi.org/10.3390/su11071912

Miles, R. E., Snow, C. S., Mathews, J. A., Miles, G., & Coleman Jr, H. J. (1997). Organizing in the knowledge age: Anticipating the cellular form. *Academy of Management Perspectives, 11*(4), 7-20. https://doi.org/10.5465/ame.1997.9712024836

Munim, Z. H., & Schramm, H.-J. (2018). The impacts of port infrastructure and logistics performance on economic growth: the mediating role of seaborne trade. *Journal of Shipping and Trade, 3*(1), 1-19. https://doi.org/10.1186/s41072-018-0027-0

Nam, H.-S., & Song, D.-W. (2011). Defining maritime logistics hub and its implication for container port. *Maritime Policy & Management, 38*(3), 269-292. https://doi.org/10.1080/03088839.2011.572705

Osadume, R. C. (2020). Port Revenue Performance and Economic Growth: The Nigerian Ports Authority Experience, 2010-2019. *LOGI–Scientific Journal on Transport and Logistics, 11*(2), 1-11. https://doi.org/10.2478/logi-2020-0010

Rausser, G., Strielkowski, W., & Štreimikienė, D. (2018). Smart meters and household electricity consumption: A case study in Ireland. *Energy & Environment, 29*(1), 131-146. https://doi.org/10.1177/0958305X17741385

Shawer, M., & Al-Ajlouni, A. (2018). Impact of profitability on stock market value: Evidence from petrochemical industry in Saudi Arabia. *Journal of Administrative and Economic Sciences, Qassim University, 11*(2), 23-47. https://ssrn.com/abstract=3340338

Silva, A. B. d. S., Araújo, A. C. d. M., Frias, P. G. d., Vilela, M. B. R., & Bonfim, C. V. d. (2021). Auto-Regressive Integrated Moving Average Model (ARIMA): conceptual and methodological aspects and applicability in infant mortality. *Revista Brasileira de Saúde Materno Infantil, 21*(1), 647-656. https://doi.org/10.1590/1806-93042021000200016

Tanzi, V. (1989). The impact of macroeconomic policies on the level of taxation and the fiscal balance in developing countries. *Staff Papers, 36*(3), 633-656. https://doi.org/10.2307/3867050

Wang, K., Hu, Q., Zhou, M., Zun, Z., & Qian, X. (2021). Multi-aspect applications and development challenges of digital twin-driven management in global smart ports. *Case Studies on Transport Policy, 9*(3), 1298-1312. https://doi.org/10.1016/j.cstp.2021.06.014