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Euro Dinar Trading Analysis Using WARIMA Hybrid Model

Elaf Alaa Al-deen Wazeer(1)

Student, Baghdad university/ Administration and Economics College/ Statistical Department, Baghdad, Iraq

elafalaaaldeen@gmail.com

Lamyaa Mohammed Ali Hameed (2)

Baghdad university/ Administration and Economics College/ Statistical Department, Baghdad, Iraq

lamiaa.mohammed@coadec.uobaghdad.edu.iq

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Abstract

The rise in the general level of prices in Iraq makes the local commodity less able to compete with other commodities, which leads to an increase in the amount of imports and a decrease in the amount of exports, since it raises demand for foreign currencies while decreasing demand for the local currency, which leads to a decrease in the exchange rate of the local currency in exchange for an increase in the exchange rate of currencies. This is one of the most important factors affecting the determination of the exchange rate and its fluctuations. This research deals with the currency of the European Euro and its impact against the Iraqi dinar. To make an accurate prediction for any process, modern methods can be used through which the model is developed. One of the most important modern methods that smooth the time series and purify it from noise is the wavelet transformation and in order to predict time series data using a new technique that combines the classic ARIMA method and the technique of Wavelet transformation, and this is called Wavelet-ARIMA hybrid model, as it was applied to data for a weekly time series of the rate of change in prices, buying and selling the European euro currency against the Iraqi dinar on the classic ARIMA model and the hybrid Wavelet-ARIMA model. The comparison was made between ARIMA and Wavelet-ARIMA models using several functions, including Haar, Db4 and Db6 to forecast the model that achieves better results for 64 weeks. As the hybrid model with Db6 function achieves better results, as the euro currency continues to increase, this negatively affects the Iraqi citizen in terms of high prices and positively on the country's economy.

Key word: ARIMA model, Wavelet-ARIMA model, Haar, Db4,Db6, Time series data analysis.

(1) elafalaaaldeen@gmail.com
(2) lamiaa.mohammed@coadec.uobaghdad.edu.iq

1. Introduction

The euro is the single currency of the European Union, which is the second most important currency after the US dollar in the international monetary system. It is controlled by the European Central Bank at its headquarters in Frankfurt, Germany. Today the euro is the official currency in 19 of the 27 countries of the European Union. It is also the official currency of six other countries that are not members of the European Union. The euro was launched on January 1, 1999, the official circulation of banknotes and coins began in 2002. The euro was used only in the financial markets and some companies. Many experts predicted that the euro might eventually rival the US dollar as an international currency.

(Nury et, al.,2017) compared the wavelet-ARIMA hybrid model with the wavelet-ANN hybrid model to study a temperature time series of northern Bangladesh. He predicted the temperature change using the wavelet collecting technique with the ARIMA random model, after analyzing the wavelet series and reconstructing it, the ARIMA model is predicted.

(Valvi and Shah، 2018) forecast the hybrid model of daily six-month time series data related to finance using the stochastic ARIMA model with the help of wavelet transform decomposition, a comparative analysis was conducted between the normal model and the proposed models.

In this research, the hybrid model of the ARIMA random model and the wavelet decomposition technique is discussed, which has been used in several fields, including image and signal processing, and so on. It uses the wavelet transform of the non-stationary time series, which contains white noise, which in turn reduces it and removes the unwanted signal in the time series data (Al-Bandar et, al.,2019) as it decomposes the series data in terms of time and frequency, which helps to conduct accurate and detailed filtering of the data (smoothing it) . To make the prediction, we will use the wavelet decomposition method using the ARIMA hybrid model, where we used the data of the weekly rate of change in the buying and selling of the European euro currency exchange against the Iraqi dinar for six years from (2015 - 2020) and the analysis was conducted for these data for 256 views, represented by: n = 2^8 . It was predicted at 64 weeks

2. ARIMA Model

The ARIMA model consists of three models, the first is the AR autoregressive model, the second model is the moving averages MA. When combined, the ARMA model becomes ARMA and three model I-integrated. In the case of the series non stationary as shown in the figure 1and 2(in page 5), we take the d differences to become the ARIMA integrated model for orders (p, I, q) where p represents the order of AR and I represents the difference and q represents the order of MA.

$$z_t = \emptyset_1 z_{t-1} + \emptyset_2 z_{t-2} + \cdots + \emptyset_p z_{t-p} + a_t \;\ldots. \quad (1)$$

It represents an AR model in (1)

$$z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \quad \ldots. \quad (2)$$

It represents an MA model in (2) (Bisgaard et. al.,2011)

$$z_t = \emptyset_1 z_{t-1} + \cdots + \emptyset_p z_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \;\ldots. \quad (3)$$

It represents an ARMA model in (3)

With the Box-Jenkins methodology, it is applied to the ARIMA model, where the order of the model can be determined by autocorrelation (ACF) and partial autocorrelation functions (PACF) , as shown in the figure 3and4 (in page5) (Al-Shaarawy, 2005).

In order to select the orders and ensure their validity, we use the criteria AIC (Akaike information criterion), BIC (Bayesian information criterion), from which we choose the best model for the lowest value of the mentioned criteria

$$AIC(k) = n \operatorname{lin} \hat{\sigma}_k^2 + 2\,k \quad .... \quad (4)$$

$$BIC(k) = n \operatorname{lin} \hat{\sigma}_k^2 + lin(n)k \quad .... \quad (5)$$

The next stage is the estimation of the parameters of the model through several methods, such as the maximum likelihood and the ordinary least squares, etc. (Box et, al.,2015). Then the fit of the model is checked by testing the estimated autocorrelation coefficients for model errors r_j using the Box-Price(Q) and Ljung-Box test, where if the probability value for (Q) is greater than the level of significance, accept the hypothesis Nothingness, that the series is stationary(That is, there are no autocorrelations to the point of error, that is, they are random numbers) , the autocorrelation of errors are independent, and the model is appropriate (Tsay,2005).

$$Q = n \sum_{j=1}^{h} r_j^2(a) \sim \chi^2_{(h-p-q)\cdot\alpha} \quad .... \quad (6)$$

The last stage is to test the efficiency of forecasting from several measures, including: Mean Absolute Percentage Error (MAPE), Mean Absolute Error(MAE) (Montgomery et, al.,2008)

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|}{n} * 100 \quad .... \quad (7)$$

$$MAE = \sum_{t=1}^{n} \left| \frac{\hat{y}_t - y_t}{n} \right| \quad .... \quad (8)$$

3. Wavelet Transform

The wavelet is a function of time and is defined $\psi(t)$ .It is described as a local waveform function . It is used to convert the signal $x(t)$ to provide more useful signal information, this analysis is known as the wavelet transform. The wavelet transform depends on the function $\psi \in L_2$(R) , also known as the mother wavelet, which is shifted and compressed in order to extract signal the mother wavelet, which are shifted and compressed in order to extract the signal specifications from its relation to time and local frequency.

To achieve the wavelet function, two conditions must be met

1. $\int_0^{\Psi} \psi(t)dt = 0$ ...(9)
2. 2. $\int_{-\infty}^{\infty} |\psi(t)|^2 \; dt = 1$ ...(10)

Father wavelet and mother wavelet are two types of wavelets that may be described as pairs of filters (Valvi et, al.,2018).

The Father wavelet is treated as a low-pass filter and the mother wavelet is treated as a high-pass filter; the low-frequency component of the time series may be separated from the high-frequency component by applying both equations 11 and 12 to the data.

$$\varphi_{J.K}(t) = 2^{\frac{J}{2}}\,\varphi(2^{J}\,t-k) \quad .k \in z.J \in z^{+} \qquad \dots (11)$$

$$\psi_{j.K}(t) = 2^{\frac{j}{2}}\,\psi(2^{j}\,t-k) \quad \dots.(12)$$

The formula may be used to explain the parameters of the mother wavelet function:

$[\,h_t\,] = [\,h_0, h_1, h_2, \dots h_{L-1}, 0, 0, \dots, 0]$ ….(13)

The formula may be used to explain the parameters of the father wavelet function (Iwok et, al.,2016):

$$g_l = (-1)^{l+1} h_{L-1-l} \qquad \dots..(14)$$

The parameters of the father and mother wavelets are calculated using the following two formulas:

$C_{J.K} = \int_{-\infty}^{\infty} f(t)\cdot\varphi_{J.K}(t)\,dt$ …. (15)

$d_{j.k} = \int_{-\infty}^{\infty} f(t)\cdot\psi_{j.K}(t)\,dt \ , j = 1, 2, \dots J$ ….(16)

$C_{J.K}$ **: Know the coefficients of approximation.** $d_{j.k}$**: Know the coefficients of details**

The wavelet function $f(\cdot)$ coefficients can be computed:

$$f(t) = \sum_{k\in z} C_{J.K}\,\varphi_{J.K}(t) + \sum_{k\in z} d_{J.k}\,\psi_{j.K}(t) + \cdots\cdots + \sum_{k\in z} d_{1.k}\,\psi_{j.K}(t) \quad \dots. (17)$$

The discrete wavelet transform is very effective for time series analysis, it analyzes the signal $f(t)$ into two parts: the approximation part represents the low-pass filter and the other part represents the high-pass filter(Ramsey,2002), and there are several filtering functions, including Haar, Daubchies and others (Ruch et, al.,2011).

1.Haar Wavelet

It is a function of the Doubchies family that represents Doubchies2 and defines the father and mother wavelet formulas as:

Father wavelet formula : Mother wavelet formula:

$$\varphi(t) = \begin{cases} 1 & 0 < t < 1 \\ 0 & o\cdot w \end{cases} \qquad ..(18)$$

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2 \\ -1 & 1/2 \le t < 1 \\ 0 & o\cdot w \end{cases} \qquad ..(19)$$

2. The Daubechies Wavelet

$\emptyset_D$ is a Doubchies scaling function. There is no exact mathematical formula linking it to complexity, but the following relationships can be used to determine this. In the case of Db4:

$$h(n) = \frac{1}{\sqrt{2}}\ \langle\, \emptyset_D(\tfrac{t}{2}), \emptyset_D(t-n) \rangle \quad n=0,1,2,\dots \quad (20)$$

h(n) :The Doubchies function's coefficients

As the coefficients h(0),h(1),….,h (3) and in the D4 state, which satisfies the following relationships are described as follows:

$$h(0) = \frac{1+\sqrt{3}}{4\sqrt{2}},\ h(1) = \frac{3+\sqrt{3}}{4\sqrt{2}},\ h(2) = \frac{3-\sqrt{3}}{4\sqrt{2}},\ h(3) = \frac{1-\sqrt{3}}{4\sqrt{2}} \qquad \ldots(21)$$

There is a unique polynomial of degree N-1 that can be represented by the functions p(y), Q(y), and can satisfy the equation:

$$(1-y)\cdot P(y) + y^N Q(y) = 1 \qquad \ldots(22)$$

Since p(y) is a polynomial, it is described by:

$$P(y) = \sum_{k=0}^{N-1}\binom{2N-1}{k}\cdot y^k \cdot (1-y)^{N-1-k} \qquad \cdots(23)$$

Since

$$Q(y) = p(1-y) \quad \ldots(24)$$

Relying on the previous properties and in order to find the coefficients D6, the polynomial is described:

$$p(y) = 1 + 3y + 6y^2 \quad ..(25)$$

The coefficients of Db6 are obtained after solving the polynomial equation and with the following values:

$h_0=0.332671$	$h_1=0.806892$	$h_2=0.459878$
$h_3=-0.135011$	$h_4=-0.085441$	$h_5=0.035226$ ..(26)

4. Hybrid Model Estimation Algorithm

Step1: The time series x(t) is decomposed using the discrete wavelet transform, after selecting a wavelet function (Haar, Doubchies 4....), we obtain the time series that comprise the time series x(t) in terms of approximations and details, as well as the formula:

$$f(t) = A_J + D_J + D_{J-1} + D_{J-2} \cdots\cdots + D_1 \quad \ldots.(27)$$

Step 2: Following the decomposition of the f(t) series, a model is constructed using the selected estimation approach, incorporating ARIMA for the approximate components A J and the detailed components D 1......D J.

Step3: When a time series model is reconstructed from its components, the predicted values will follow the following relationship (Kumar et, al.,2015) :

$$\hat{y}(t) = A_J^{ext} + D_J^{ext} + D_{J-1}^{ext} + \cdots\cdots + D_1^{ext} \qquad \ldots(28)$$

5.The Application

First, the model's identification: Figures 1 and 2 illustrate the graphic of the data from the original series and the data after taking the first difference to achieve stationary. A Dickey-Fuller test for stationary was performed after the first difference, and it was found that there is no unit root, as determined by ACF and PACF ranks and tested using the comparison criteria AIC and BIC. The best model for identifying the model that obtains the lowest value of the criterion is of the order ARIMA (2, 1, 0).

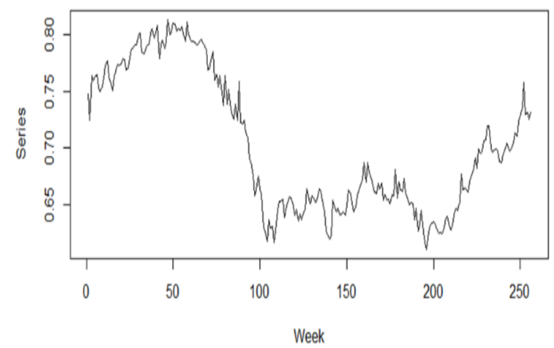

Figure 1: Original Data

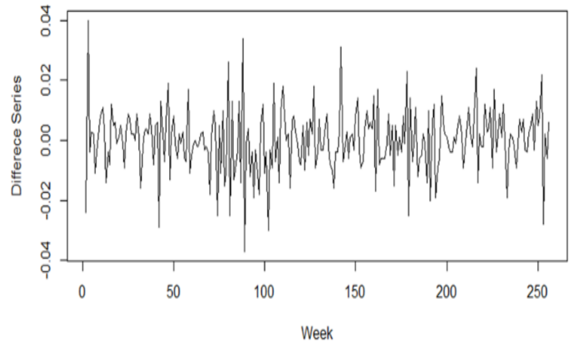

Figure 2: After first difference Data

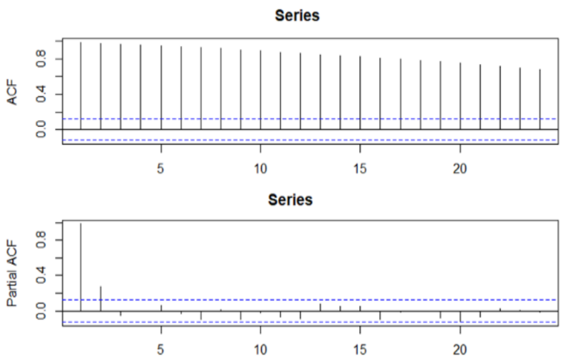

Figure 3: ACF and PACF of Data

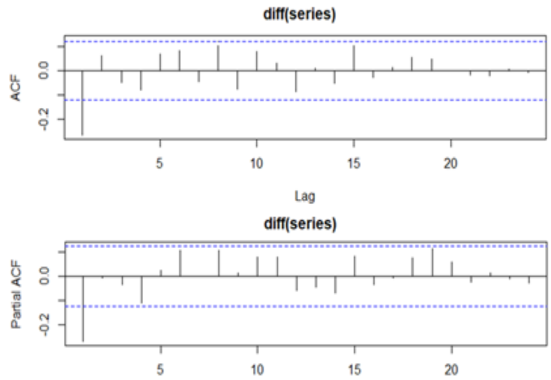

Figure 4: First differenced ACF and PACF of Data

Second, estimation: the best model's parameters were estimated using the ordinary least squares method.
Third, checking the fit : using the Lujng-Box test to test the autocorrelation coefficients of errors and comparing the p- value with the significance level of 0.05, accept the alternative hypothesis, which means that the error autocorrelations are independent and random, and the series is stationary, as shown in Figure 5 (Wei,2006).

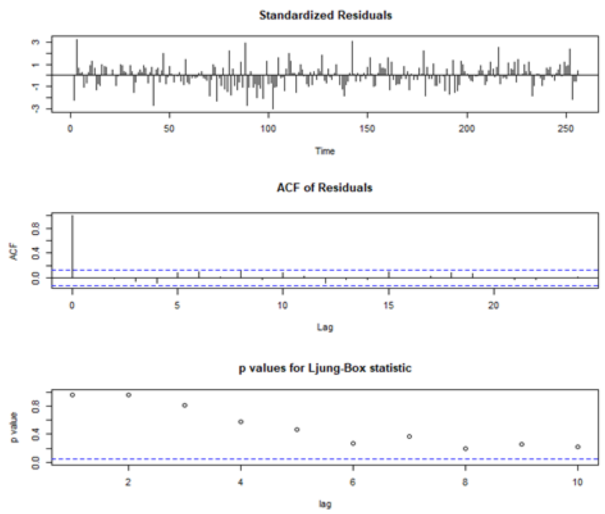

Figure5: Standardized Residual, residual autocorrelation, and probability values

6. Hybird Models

The levels test was performed for the Haar, Db4 and Db6 wavelet functions as mentioned earlier in equations 18,19,20 and 25 , and the optimal level to smooth the data was chosen using some comparison measures MAE and MAPE through Table (1). The best level of the Haar function turns out to be the third level, with the first level being the Db4 function and the second level being Db6.

Table (1) Function levels

Level	Haar-Wavelet		Db4-Wavelet		Db6-Wavelet	
	MSE	MAPE	MSE	MAPE	MSE	MAPE
1	2.56036e-05	0.6912568	0.3756831	0.7281421	5.19841e-05	0.9849727
2	7.56250e-06	0.3756831	4.71969e-05	0.9385246	3.19225e-05	0.7718579
3	5.61690e-06	0.3237705	4.65124e-05	0.9316940	3.21489e-05	0.7745902
4	6.50250e-06	0.3483607	4.78864e-05	0.9453552	3.27184e-05	0.7814208

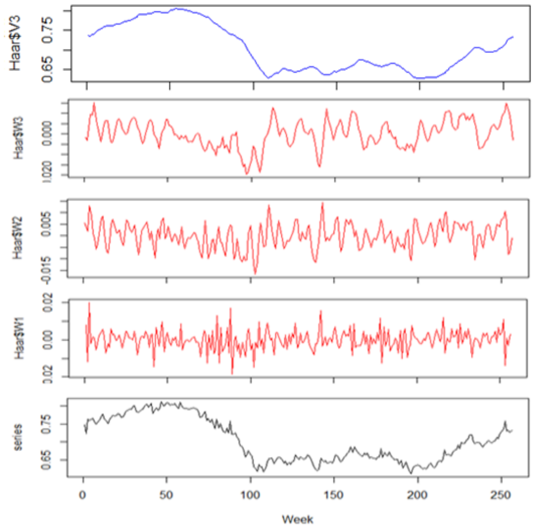

Figure 6: Haar-ARIMA

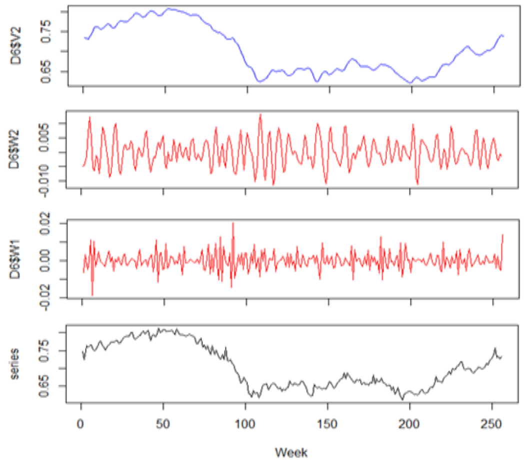

Figure 7: Db6-ARIMA

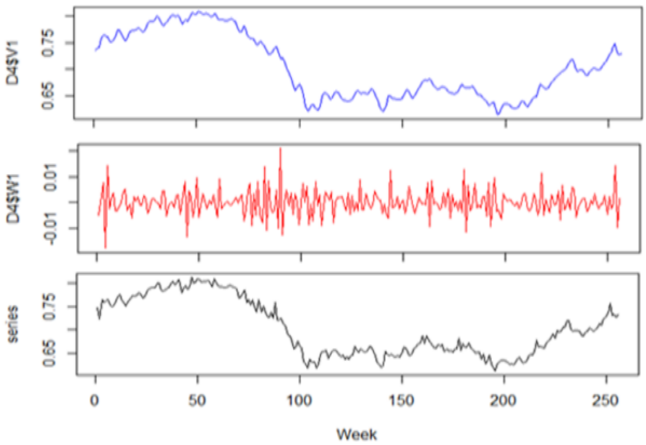

Figure 8: Db6-ARIMA

Table (2) Shows the order of each hybrid function :

Table (2) Hybird function orders

Function	Haar-Wavelet	Db4-Wavelet	Db6-Wavelet
Order	(2,1,0)	(0,1,1)	(5,1,3)
AR(1) AR(2) AR(3) AR(4) AR(5) DIFFRINCE	-0.2724 0.0003 1	 1	0.2614 -0.2046 0.3677 0.0588 0.3646 1
MA(1) MA(2) MA(3)		1	-0.5164 0.4031 -0.6569

As shown in Figures 6, 7 and 8, the Box Jenkins methodology has been applied to the segmented string (i.e. after separating the original string) into two components representing the low-pass filter AJ and detail representing the high-pass filter DJ as in equation (28) and for all mentioned wavelet functions previously. Then choose the best prediction model by comparing the hybrid models with the classic ARIMA model using the comparison criterion AIC, BIC, MSE, MAPE and RMSE metrics as shown in Table (3).

Table (3) Standards of comparison, error measures and test statistics (Liung-Box)

Models	AIC	BIC	Q-TEST	MAE	RMSE	MAPE
ARIMA	-1609.17	-1598.55	13.166	0.007790921	0.01017279	1.1159
Haar-Wavelet	-1609.17	-1598.55	13.166	0.007790921	0.01017279	1.1159
Db4-Wavelet	-1610	-1602.92	18.15	0.007887108	0.01019713	1.134882
Db6-Wavelet	-1640.79	-1608.92	7.872	0.007125505	0.009312506	1.02223

The hybrid Db6-wavelet model is of order 5 according to the preceding table and comparison criteria, and it represents the best prediction model, as shown in Table 2 and represented with the formula:

$$z_t = 0.2614z_{t-1} - 0.2046z_{t-2} + 0.3677z_{t-3} + 0.0588z_{t-4} + 0.3646z_{t-5} - 5164a_{t-1} + 0.4031a_{t-2} - 0.6569a_{t-3} \quad \dots (29)$$

For a period of 64 weeks, the weekly rate of change in the buying and selling prices of the euro against the Iraqi dinar was forecast.

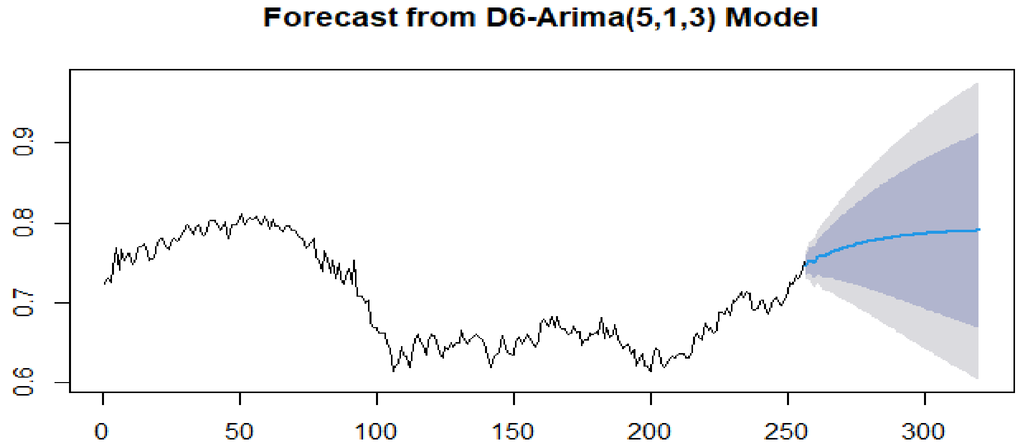

Figure 9: Predict the weekly rate of change between the exchange rates for buying and selling the euro currency The European exchange for the Iraqi dinar

6. Conclusion:

Using on wavelet decomposition and the ARIMA model, a modern and thorough method for time series prediction has been developed. The original time series is hierarchically segmented into a new time series that performs better than the original. As a result, the classical ARIMA model can better forecast the future value of the collection of decomposing series.

Table 3 shows that the hybrid Haar-wavelet model performs similarly to the conventional ARIMA model, with nearly identical results, The Hybrid Db4 is better than the Haar Hybrid, but the hybrid Db6-wavelet model is the best predictor for the weekly rate of change as shown in Figure 9 gradually increases and starts with a value of 0.7469408 to 0.789988 for a period of 64 weeks using formula 3, 29 , showing that the hybrid model predicts more effective work than the classical method.

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تحليل تداول اليورو بالدينار بإستعمال إنموذج WARIMA الهجين

إيلاف علاء الدين وزير[1]
العراق-جامعة بغداد - كلية الادارة والاقتصاد -قسم الاحصاء
elafalaaaldeen@gmail.com

م.د. لمياء محمد علي حميد[2]
العراق-جامعة بغداد - كلية الادارة والاقتصاد -قسم الاحصاء
lamiaa.mohammed@coadec.uobaghdad.edu.iq

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مستخلص البحث

إن ارتفاع المستوى العام للأسعار في العراق يجعل السلعة المحلية أقل قدرة على منافسة السلع الأخرى ، الأمر الذي يؤدي إلى زيادة حجم الواردات وانخفاض حجم الصادرات ، حيث يؤدي إلى زيادة الطلب على العملات الأجنبية بينما يتناقص. الطلب على العملة المحلية. مما يؤدي إلى انخفاض سعر صرف العملة المحلية مقابل زيادة في سعر صرف العملات وهذا من أهم العوامل المؤثرة في تحديد سعر الصرف وتقلباته. يتناول هذا البحث عملة اليورو الأوروبي وتأثيرها على الدينار العراقي. لعمل تنبؤ دقيق لأي عملية ، يمكن استخدام الأساليب الحديثة التي يتم من خلالها تطوير النموذج. من أهم الطرق الحديثة التي تطور عمل السلاسل الزمنية وتنقيتها من الضوضاء هي التحويل المويجي ، ومن أجل التنبؤ ببيانات السلاسل الزمنية باستخدام تقنية جديدة تجمع بين طريقة ARIMAالكلاسيكية وتقنية التحويل المويجي ، وهذا هو يسمى نموذج Wavelet-ARIMA الهجين ، حيث تم تطبيقه على بيانات سلسلة زمنية أسبوعية لمعدل التغير في أسعار البيع والشراء لعملة اليورو الأوروبية مقابل الدينار العراقي على إنموذج ARIMA الكلاسيكي وإنموذج Wavelet-ARIMA الهجين. تم إجراء المقارنة بين نماذج ARIMA و Wavelet-ARIMA وبإستعمال دوال عدة منها Haar و Db4 وDb6 ، والتنبؤ بالنموذج الذي يحقق نتائج أفضل لمدة 64 أسبوعًا،اذ ان الانموذج الهجين بدالة Db6 يحقق نتائج أفضل و باستمرار ارتفاع عملة اليورو ذلك يؤثر سلبا على المواطن العراقي من حيث ارتفاع الأسعار وإيجابا على اقتصاد البلاد .

المصطلحات الرئيسة للبحث: نموذج ARIMA ، نموذج Wavelet-ARIMA ، Haar، Db4 ، Db6 ، تحليل بيانات السلاسل الزمنية.

*البحث مستل من رسالة ماجستير

[1] elafalaaaldeen@gmail.com
[2] lamiaa.mohammed@coadec.uobaghdad.edu.iq