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A Hybrid Model for Financial Forecasting Based on Maximal Overlap Discrete Wavelet Transform; Evidence from Chinese Exchange Rates.

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Abstract:

In some time series, especially financial time series, the high/low frequency sometimes occurs in short time scale, or for a specific period, the phenomena happen such that not observed in the rest of the time series; in the situation, decomposition of the time series into constitutive series can be very useful ,because the wavelet transform has the ability to transform the time series into low-and-high-frequency information, which allows detecting trends, breakdown points, and discontinuities in the data that may it is lost when other analysis methods are used. to cope with non-stationary time series forecasting and with the aim of improving the forecasting accuracy of the volatility pattern in exchange rates , we use the wavelet transform with hybridization methodology to build a hybrid model combining Maximal Overlap Discrete Wavelet Transform (MODWT), Autoregressive Integrated Moving Average (ARIMA), GJR-GARCH model and Radial Basis Function Neural Network(RBFNN) model, so that it is capable of capturing the volatility in financial time series, by applying it to the Chinese Yuan exchange rate for the period (2015/1/5 to 2022/11/11) , where the wavelet transform technique provides a useful feature based on data analysis, which improves the performance of the model. The time series of exchange rates were analyzed into their (approximation and detailed) coefficients at three levels using the Maximal Overlap Discrete Wavelet Transform (MODWT). The experimental results of this research demonstrate that the proposed model has a higher prediction accuracy than the single models (SVR and RBFNN) and other hybrid models (MODWT-ARIMA-GJR-GARCH-SVR and ARIMA-GJR-GARCH).

Paper type: Research paper.

Keywords: Maximal Overlap Discrete Wavelet Transform (MODWT), Radial Basis Function Neural Network (RBFNN), Support Vector Regression (SVR), Autoregressive Integrated Moving Average, GJR- GARCH.

1. Introduction:

Many statistical studies, especially those related to the economic side, suffer from rapid fluctuations in data that make the prediction process complex, as a high frequencies are dealt with using Fourier transform and thus we lose the ability to deal with low fluctuations, despite the use of these transformations and the use of many models that deal with fluctuations, including ARCH models, but they are not perfect because we lose several properties in the series that may be a door to improve forecasting.

Forecasting is extremely important for researchers who are active in the areas of analysis and forecasting of financial time series (Gherman et al, 2012), and since the aim of the study is to predict exchange rates, therefore it must be mentioned that accurate prediction of exchange rates is a great challenge, as People can't understand what's going correctly after a few moments, which it makes predicting what will happen in the future a problem in many areas, especially in the financial markets (Ghaeini et al, 2018).

Since financial and economic time series exhibit time-varying frequencies, wavelets may be a good approach for analyzing time series (Gherman et al, 2012), the wavelet transform has gained great importance in many fields such as engineering, physics, and signal processing, as it allows the extraction of important hidden information and important temporal features of the original time series (Chandar et al, 2016).

Wavelet transform is used to provide robustness to forecasting models. using wavelet transform, The time series is decompose into different components (approximate and detailed) and wavelet components that are obtained are very useful for improving the forecasting ability of the model by obtaining useful information at different levels, which leads to forecasting models by dealing with fluctuations High and low, which makes the noise to which the series is exposed to as little as possible. After that prediction is made using an appropriate model for each sub-series based on their feature. Instead of applying time series models, both linear and non-linear and artificial intelligence models directly to the input data, they are applied individually to the sub-series resulting from the analysis (Kumar et al, 2017).

Due to the volatility in exchange rates, Linear time series models are incapable of capturing the fluctuations in prices, which makes them insufficient to predict future exchange rates. While nonlinear time series models are good at capturing fluctuations in price series, They are extremely complex, necessitating a hybrid model is used that combines both linear and non-linear time series models and artificial intelligence models to predict the Chinese Yuan exchange rates. Because of the importance of forecasting, many models have been used with wavelet transform starting with the use of wavelet transform with ARIMA models, after using the wavelet transform with linear models, it was used with hybrid models that are based on both linear and non-linear models, since time series consists of both linear and non-linear components at the same time, the model (ARIMA-GJR-GARCH) has been applied to time series is nonlinear and non-stationary, and has time-varying variance. The wavelet transform was also used with artificial intelligence (AI) and machine learning algorithms to deal with financial data.

In this paper we aims to improve prediction accuracy by proposing a hybrid prediction model based on wavelet transform of type MODWT. First, the wavelet transformation was used to decompose the price series into detailed and approximation series, then both ARIMA-(GJR-GARCH) and RBFNN models were used to predict the approximate and detailed series, respectively. Finally, to verify whether the proposed model is effective for predicting exchange rate, the proposed model is compared with the classical model.

1.1 Literature Review:

In the resent years there are number of researchers tries to improve prediction accuracy by used many techniques Ye (2017) studied to propose a hybrid forecasting method that applies the hybrid model (ARIMA-SVR) with Discrete Wavelet Transform in order to improve predictions in the closing price series. Compared with single models (ARIMA, SVR) the results of the study showed that the proposed model is an effective method for prediction, which greatly improves the prediction accuracy. Ghaeini et al (2018) studied to proposed a hybrid model consisting of wavelet transform, ARMA-GARCH, and Artificial Neural Network (ANN), It was applied to a daily price series of 15 stocks from the New York Stock Exchange. For the period (24/6/2015 to 10/11/2017).the study's findings showed the superiority of proposed model through comparison with the following models (ANN,ARIMA-ANN,ARIMA-GARCH) based on the comparison criteria. Ahasan et al (2019) aimed to enhance forecasting performance in global climate data series, based on wavelet transform with GARCH (1, 1) model. The results of the study were shown by comparing the proposed model with GARCH model and applying on Multivariable ENSO Index (MEI) from January 1950 to February 2018, that the proposed model gives better forecasts accuracy than GARCH based on the comparison criteria. KU and Kovoor (2020) proposed model for forecasting wind speed through combining the wavelet transform features of type DWT and the hybrid model (LSTM-SVR), wind speed data was obtained from India's National Energy Institute for the period (01-10-2013) to (30-09-2017). The proposed model was compared to each of the models (LSTM, ARIMA), it was found that the proposed wavelet-based hybrid model gives better forecast accuracy. Zeng and Khushi (2020) proposed a model that combine both wavelet transform of type DWT, Attention-based Recurrent Neural Network (ARNN) and ARIMA model. Applied to exchange rates USD/JPY for the period (01-01-2019) to (31-12-2019), the results of the study proved, through comparison with many models (SVR, LSTM, ARNN, ARNN-ARIMA), that the proposed model gave better performance. Pourghorb and Mamipour (2020) provided an approach for modeling and forecasting the electricity prices based on complex features. The proposed method (Wavelet-ARIMA-GARCH) was applied to the average daily data of electricity prices in Iran for period (Spring 2013 to Winter 2018), The study's proved demonstrated that the hybrid model based on wavelet transform of type DWT had better performance than the classical hybrid model (ARMA-GARCH) also the suggested model can better and more precisely capture the complex features of electricity prices. Fan et al (2021) studied proposed a hybrid model for predicting air quality based on DWT (Wavelet –LSTM-ARMA).Data on air quality from six Environmental Protection Bureau environmental monitoring stations in Tangshan city were collected for the period (1 May 2018 to 1 August 2019) is used in this study .the results of the study proved that the proposed model through comparison with many models (ARMA, LSTM, W-LSTM) is the most suitable for predicting air quality. Mohammed and Ahmed (2023) studied compare between ARIMA model and wavelet-ARIMA model. The results of the study were shown by comparing the models and applying on wind speed (m/s) data sets are acquired from the Sulaimani meteorological directorate for the period (January 2016-December 2020), that the Wavelet-ARIMA gives better forecasts accuracy than ARIMA based on the comparison criteria.

The research problem it is that financial time series suffer from rapid fluctuations that make the forecasting process complicated, and despite the use of many transformations and models that deal with fluctuations including among the transformations and models that deal with fluctuations, including the Fourier transform, which deals with high frequencies and thus losing the ability to deal with low frequencies, which leads to a loss several properties of time series. Therefore, the objective is to improve prediction accuracy by proposing a hybrid prediction model based on wavelet transform of type MODWT.

2.Material and Methods:

2.1 Data :

This section uses the Chinese Yuan's 2050 daily exchange rate. These data cover the period from November 11, 2022, to January 5, 2015.Every observation was obtained from the Central Bank of Iraq. The data are divided into training and testing categories based on the observations, with the training data spanning from 2015/01/5 to 2022/06/28) and the testing data spanning from 2022/06/31 to 2022/11/11.

2.2 Wavelet Transform:

In order to overcome the shortcomings of the short-time Fourier transform (STFT), What is known as "Wavelet Transform" has been developed, which has become one of the most important and powerful tools for signal representation (Zhiping, 2009).the wavelet transformation is based on the use of a variable width window instead of a fixed width window along the signal, meaning that the division of the frequency window into time is variable, and the figure1 shown wavelet transform. Although The wavelet transform converts a signal from the time domain to the time- scale domain, but because this process also decomposes the original signal into several other signals with varying levels of resolution, this process is referred to as "signal decomposition" (Vaičiūnaitė, 2021).thus ,the wavelet transform can be defined as "It is a pre-processing function that allows the wavelet filter to move across the time series data before decomposing the main series into subseries with a local time and frequency domain in order to discover the property of the time series" (Signal)(Al Rababa'A, 2017).

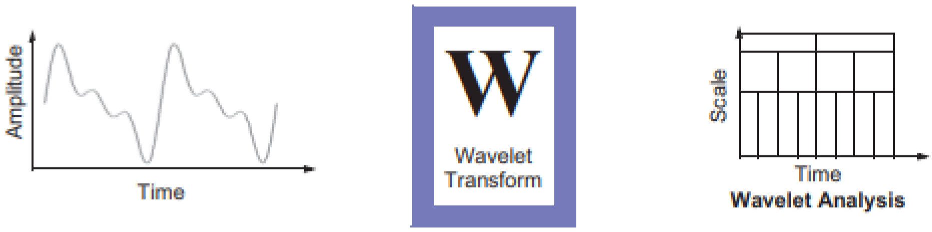

Figure 1: Wavelet Transform (Misiti et al, 2022)

There are three types of wavelet transforms: continuous wavelet transforms (CWT), discrete wavelet transforms (DWT) and maximum overlapping wavelet transform (MODWT). The primary distinction between MODWT and DWT is that the former can be applied to any size of data, whereas the latter can only be applied to a limited number of data (the number of observations must be two powers of J) (Alshammari et al, 2020). Additionally, unlike the DWT, the MODWT is not orthogonal; as a result, it is thought to be extremely redundant given the intuitive knowledge it offers about the signal (Anjoy and Paul, 2017). We will utilize MODWT in this paper due to its increased flexibility and modernity (Alshammari et al, 2020). A mathematical model called wavelet analysis enables the input price series to be divided into multiple frequency bands (Chandar et al, 2016). The time series is decomposed into two components: the mother wavelet (wavelet functions) represents high frequencies and is also referred to as detailed coefficients; this component eliminates any trends in the series but, more crucially, is sensitive to jumps and spikes in data (Alshammari et al, 2020). The father wavelet (scaling function) represents the low frequency and is also known as the approximate part or the smooth coefficients. It is a smoother approximation of the original series and keep track of many features of the data set, including trends. According to the definition given above, the mother wavelets "play a role similar to sines and cosines in the Fourier decomposition. They are either compressed or dilated in time domain to generate cycles fitting to the actual data" (Kumar et al, 2011). In the J-level wavelet decomposition, the mother wavelet and father wavelet, respectively, are as follows: As of (Dghais,2016):

$$\psi_{(j,k)} = 2^{-j/2}\, \psi\left(\frac{t-k2^j}{2^j}\right) \qquad (1)$$
$$\varphi_{(j,k)} = 2^{-j/2}\, \varphi\left(\frac{t-k2^j}{2^j}\right) \qquad (2)$$

A J-level wavelets decomposition is obtained with $j = 1,2,\ldots,J$ where J is the number of multiresolution levels or (scale), k represent ranges from 1 to the number of coefficients in the specified components. As mentioned above, the wavelets above satisfy (Alshammari et al, 2020):-

$$\int \psi_{(j,k)}\, dt = 1$$
$$\int \varphi_{(j,k)}\, dt = 0$$

Wavelet coefficients are used to compute the decomposition, and this process is represented by the general mathematical model that follows (Kumar et al, 2011; Alshammari et al, 2020):

$$d_{(j,k)} = \int \psi_{(j,k)} x(t)dt, \quad s_{(j,k)} = \int \varphi_{(j,k)}\, x(t)dt$$

Whereas; $d_{(j,k),}\ s_{(j,k)}$ they represents wavelet transform coefficients.
And In more details (Kumar and Joshi, 2011):

$$x(t) = \sum_k s_{(J,k)}\varphi_{(j,k)}(t) + \sum_k d_{(J,k)}\, \psi_{(j,k)}\, (t) + \cdots + \sum_k d_{(j,k)}\, \psi_{(j,k)}(t) + \sum_k d_{(1,k)}\, \psi_{(1,k)}(t) \; (3)$$

$$V_J = \sum_k s_{(J,k)}\varphi_{(j,k)}(t)$$
$$W_J = \sum_k d_{(J,k)}\, \psi_{(j,k)}(t)$$

Thus, the multi-resolution analysis of the original series $x(t)$ is acquired by combining both approximation series V_J and the detailed series W_J, as follows in eq(4):

$$x(t) = \sum_{j=1}^{N} w_j \; + v_J \qquad (4)$$

The reason for using MODWT in our research is that DWT suffers from drawbacks, such as:

- The sample size must be base 2, i.e. requires a series with a dyadic length $N = 2^J$. (Masset, 2008; Anjoy et al, 2017)
- DWT is not shift invariant, i.e. If the series is shifted one period to the right, the multiresolution coefficients will be different.(Masset, 2008)

Numerous wavelet types, including Haar, Daubechies, Morlet, and Mexican Hat, can be used to forecast financial time series; however, in this study, we will employ the Haar wavelet function (Chandar et al, 2016), since we know that the decomposition levels equal 3.

2.3 Autoregressive Integrated Moving Average Model (ARIMA):

Time series modeling is necessary for time series forecasting; Box and Jenkins proposed the following random time series models: AR, MA, ARMA, and ARIMA (Lv and Yue, 2011). We use the ARMA model for stationary time series; however, if the ARMA model is applied to non-stationary series, the time series must be transformed into a stationary series by taking its differences (Lv and Yue (2011); ALhameed, 2020). The representation of the ARMA(p,q) model is as follows in eq(5) (Alsommari et al, 2020):

$$\emptyset_p(B)y_t = \theta_q(B)\varepsilon_t \qquad (5)$$

Here, y_t denotes the time series observation at time t, B denotes the back shift operator, and ε_t random error $\varepsilon_t \sim N(0, \sigma^2)$ (Alshammari et al, 2020). According to (Lv and Yue 2011), the ARIMA (p,d,q) model is represented as follows in eq(6):

$$\emptyset_p(B)\Delta^d y_t = \theta_q(B)\varepsilon_t \qquad (6)$$

where d is the number of times a series needs to be differenced in order to induce stationarity (Okasha and Yaseen, 2016), q is the term of moving average, and p is the autoregressive term (Hongguang, 2016). All other values are non-negative integers.

2.4 GJR-GARCH Models:-

One of the volatility models suggested to address asymmetric effects is the asymmetric GARCH model, which Glosten, Jagannathan, and Runkle introduced in 1993 (Kumar et al, 2017). One benefit of the GJR-GARCH model is its ability to quantify volatility resulting from the various impacts of both positive and negative news (Hidayana et al, 2021). The GJR model illustrates the asymmetry in volatility in response to positive and negative shocks, much like the EGARCH model does (Rashedi et al, 2020). Parts of the GJR-GARCH model reflect asymmetrical properties, which sets it apart from the GARCH model. I intended By incorporating the indicator, the model effectively captures the asymmetrical nature of a time series (Andersson and Haglund, 2014), GJR-GARCH (p,q) model can be expressed as follows in eq(7) (Uddin et al, 2021):-

$$h_t = \sigma_t{}^2 = w + \sum_{i=1}^{p} \alpha_i \in^2{}_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{i=1}^{p} \gamma_i I_{\in_{t-i}} \in^2{}_{t-i} \qquad (7)$$

Where α_i represents the ARCH parameter, β_j the GARCH leverage effect parameter, and γ_i the leverage effect parameter, $I_{\in_{t-i}}$: is an indicator function that takes 1 when $\in_{t-i} < 0$ and takes zero otherwise.

$$I_{\in_{t-i}} = \begin{cases} 1 & if \quad \in_{t-i} < 0 \\ 0 & if \quad \in_{t-i} \geq 0 \end{cases} \qquad (8)$$

Negative error does not operate if parameter $\gamma_i > 0$ suggesting that the impact of bad news will outweigh the impact of good news (Hidayana et al, 2021). According to (Nooruldeen et al, 2022), the GJR-GARCH process is stationary if and only if

$$\sum_{i=1}^{p}\left(\alpha_i + \frac{\gamma_i}{2}\right) + \sum_{j=1}^{q} \beta_j < 1$$

2.5 Radial Basis Function Neural Network (RBFNN):

The machine learning community has shown a great deal of interest in RBF networks because of their excellent performance and attractive theoretical properties (Que and Belkin, 2016). RBF neural network techniques have drawn a lot of attention and have been suggested as potent computational tools for resolving the forecasting problem (Chang, 2013). RBF neural networks first appeared as a type of artificial neural network in the late 1980s, created by Moody and Darken (Zainudin et al, 2015). Numerous scientific and engineering domains have made extensive use of RBFN networks (Yue and He, 2007). Because it uses the radial basis activation function, the network is known as RBFNN (Pandey et al, 2020). For pattern classification and regression, RBFNN modeling combines supervised and unsupervised learning (Amerian and Schwenker, 2020). Due to its varied performances, this network has developed into one of the most popular network types and is now among the most competitive networks for multilayer perceptron (MLP) networks (Yu et al, 2008). Although the architecture of RBFNN and MLP are similar, there are some differences (Vaičiūnaitė, 2021).

- RBFNN can't have more than one hidden layer, is often easier to be trained than MLP. As a result, RBFNN is an alternative to the more widely used MLP network and is less computer time consuming for network training (Zainudin et al, 2015).
- The hidden nodes uses radial basis functions (RBF) as the identity activation functions.

According to Figure 2 (Zainudin et al, 2015), the fundamental structure of an RBFNN is a three-layer network with an input layer, a hidden layer, and an output layer. Each hidden unit performs a radial activation function, and each output unit performs a weighted sum of the outputs of hidden units (Yue and He, 2007) (Amirian and Schwenker, 2020). The input layer only distributes input to the hidden layer; it has no weights. Any of the many unsupervised learning methods can be used to train it (Zainudin et al, 2015). A non-linear link connects the input space and the larger space, forming the second layer (Sharifi and Abyaneh, 2014). Each node in the hidden layer determines the Euclidean distance to the input (Pandey et al, 2022) and a radial basis function modifies the result (Kia, 2012).Typically, an activation function of the (Gaussian) type is a radial basis function (Chen et al, 2016). Ultimately, the output layer multiplies the outputs of the hidden layer by weights (Pandey et al, 2020). In other words, all of the inputs from the hidden layer are gathered in the output node to generate the final output of the RBFNN (Yu et al, 2008; Kia, 2012):-

$$Y = f(x) = \sum_{i=1}^{N} W_i \emptyset(D_i) + w_o \quad (9)$$

where N is the number of nodes in the RBFN's hidden layers, w_o is the bias, w_i is the weight parameter, and $\emptyset(D_i)$ is the RBF used as an activation function. As you can see, in this study, we used the Gaussian function as the RBF approach:

$$\emptyset(D_i) = e^{-D^2{}_i / \sigma^2} \quad (10)$$

According to (Yue and He (2007) the width of the radial basis function is represented by σ, and the distance between vector X and the hidden layer node's center is represented by D_i (Kia, 2012). The Euclidean average method is commonly used to compute distance in the following manner:

$$D_i = \sqrt{\sum_{j=1}^{k} (x_j - c)^2} \quad (11)$$

Where, the input vector is x.
For the nodes in the hidden layer, C is the cluster center.

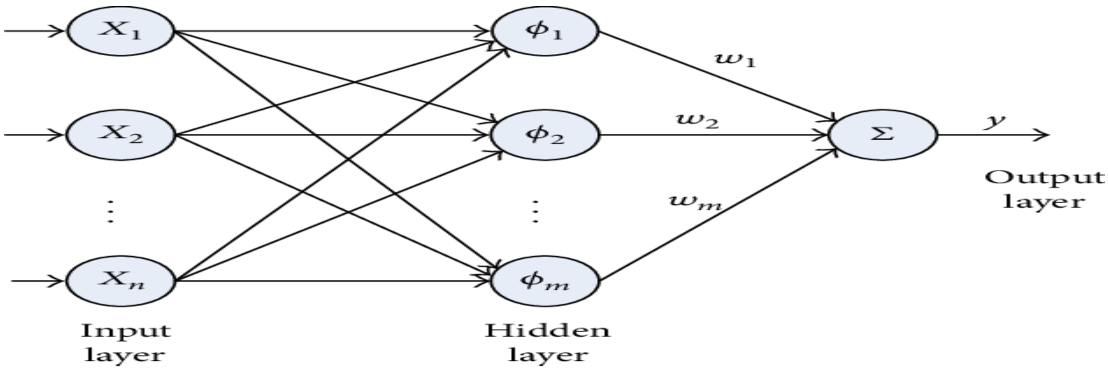

Figure 2: Structure of the Radial Basis Function Network

2.6 Accuracy criteria :

The accuracy of forecasts is evaluated using a variety of accuracy criteria. The best forecasting model is chosen using the Mean Square Error (MSE) as the selection criterion. This is because the majority of research has shown that the model that is chosen need not be the model that produces the best forecasts. It would be thought that the model with the smaller value is superior and more suitable. (Edward, 2011; Pahlavani and Roshan ; 2015;Kazem, 2016).

1- Mean Square Error (MSE) :

The average of the squared difference between the actual and forecast values is what this accuracy metric measures.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t) \qquad (12)$$

Where t=1, 2,…,n

y_t Represents actual value. $\hat{y}_t$ Represents forecast value.

2.7 Research Design and Methodology :

With increasing forecast accuracy being the main focus of the research, a hybrid ARMA-GARCH-RBFNN model based on MODWT was developed to increase forecast accuracy for exchange rates. The following are the suggested hybrid method's primary steps:

• Step 1: we adopt Maximal Overlap DWT to decomposed exchange rate series into approximation components(background series) and detailed components(details series)(Wang and Jing, 2003), taking into account the type of wavelet used and the number of decomposition levels, Haar wavelet transform is the type of wavelet used in this paper. and the level of decomposition is 3 according to INT [$\log(N)$] where N represents number of time series observation , INT: represents integer number $\log(N)$: is common logarithm (Sehgal et al, 2014)

• Step 2: By wavelet reconstruction, the transformed version of the original series is obtained, the approximate and detailed series respectively v_3, w_1, w_2, w_3 are called V_3, W_1, W_2, W_3 ,and thus the relation among the approximate and detail signals is expresses as follows :(Lv and Yue, 2011;Pourghorban and Mamipour, 2020).

$$x_t = V_3 + W_1 + W_2 + W_3 \quad (13)$$

The decomposed components can mine the potential information in the data more precisely and effectively than the original signal could (Vaghasia, 2018).

• Step 3: an appropriate model is chosen to predict the sub-series obtained based on their features. The approximate series V_3 that represents the price trend is predicted using the hybrid (ARIMA -GJR-GARCH) model, while the detailed series W_1, W_2, W_3 that contain information related to the noise content of the original signal are predicted using a machine learning method , here we use RBFNN.

• Step 4: by combining both detailed and approximate series predicted the final predicted price is obtained.

• Step 5: the proposed hybrid model based on MODWT is compared to single models such as SVR which is currently widely used in time series and classical hybrid models to see if the proposed model is capable of improving prediction accuracy.

3. Discussion of Results :

since the goal of the research is to improve prediction accuracy, therefore, in this article, first work will be carried out in many stages: **in the first stage**, the price series is decompose using the Haar function into approximate series whose pattern is similar to the original series and three detailed series as shown in figure3.

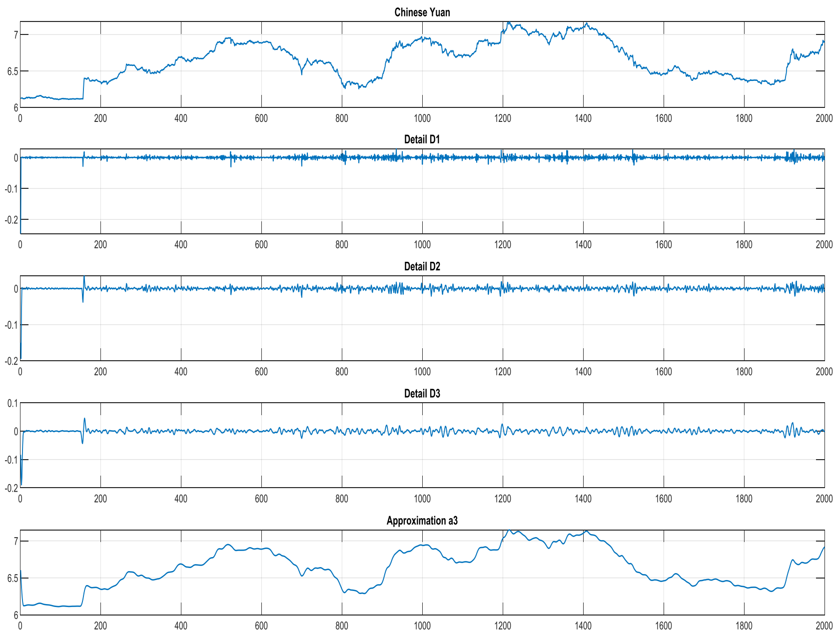

Figure 3: Decomposing the data using MODWT based on Haar function

In the **second stage** is applied the hybrid model (ARIMA-GJR-GARCH) to the approximate series; after applying several ARIMA models, they are compared to choose the appropriate ARIMA(1,1,3) model that gave the lowest values for the comparison criteria, then the GJR-GARCH model with different orders is applied to the residuals of the ARIMA(1,1,3) model, the fitted GJR-GARCH model should be selected in table 1.

Table 1: Selecting the fitted GJR-GARCH model

Models	AIC	SIC
GJR-GARCH(1,1)	-12.44357	-12.42160
GJR-GARCH(1,2)	-12.46860	-12.44388
GJR-GARCH(2,1)	-12.51797	-12.49051
GJR-GARCH(2,2)	-12.56790	-12.53768

Then the above table will show that GJR-GARCH (2,2) is the fit model since it has lass AIC and BIC, and the Table 2 shows parameters of ARIMA(1,1,3)-GJR-GARCH (2,2) that was chosen as the best final model to represent the approximate series (A3).

Table 2: shows parameters of ARIMA(1,1,3)-GJR-GARCH (2,2)

Dependent Variable: DPRICE				
Method: ML ARCH - Normal distribution				
Date: 10/24/23 Time: 20:49				
Sample (adjusted): 1/07/2015 11/11/2022				
Included observations: 2048 after adjustments				
Convergence achieved after 41 iterations				
MA Backcast: 1/02/2015 1/06/2015				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RESID(-1)^2*(RESID(-1)<0)				
+ C(8)*RESID(-2)^2 + C(9)*RESID(-2)^2*(RESID(-2)<0) + C(10)				
*GARCH(-1) + C(11)*GARCH(-2)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	0.948168	0.006542	144.9398	0.0000
MA(1)	0.993678	0.004969	199.9737	0.0000
MA(2)	0.907837	0.010283	88.28580	0.0000
MA(3)	0.910024	0.008031	113.3169	0.0000
	Variance Equation			
C	1.85E-08	1.16E-09	15.95020	0.0000
RESID(-1)^2	0.112584	0.017612	6.392293	0.0000
RESID(-1)^2*(RESID(1)<0)	-0.062623	0.024620	-2.543523	0.0110
RESID(-2)^2	0.277141	0.027403	10.11357	0.0000
RESID(-2)^2*(RESID(2)<0)	0.123580	0.029704	4.160384	0.0000
GARCH(-1)	-0.053960	0.010193	-5.294003	0.0000
GARCH(-2)	0.621435	0.014879	41.76647	0.0000
R-squared	0.990609	Mean dependent var		0.000128
Adjusted R-squared	0.990595	S.D. dependent var		0.008070
S.E. of regression	0.000783	Akaike info criterion		-12.56790
Sum squared resid	0.001252	Schwarz criterion		-12.53768

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Log likelihood	12880.52	Hannan-Quinn criter.		-12.55682
Durbin-Watson stat	1.628425			
Inverted AR Roots	.95			
Inverted MA Roots	.00-.95i	.00+.95i	-1.00	

The next step is to predict of 10% of the observations.in contrast, RBFNN model is applied to all detailed series (D1,D2, D3), it is also predicted for 10% of observations. And then we will combine predictions for every series to get the hybrid model. By contrasting the single model RBFNN with the suggested model based on MODWT and other hybrid model ARIMA-GJR-GARCH to verify whether the proposed model is able to improve the prediction accuracy and compare proposed model with other models (single and hybrid) based on several prediction algorithms (SVR, MODWT-ARIMA-GJR-GARCH-SVR) to ensure if the prediction framework is valid (Wang et al, 2019) , the experimental results in table (3) show that the proposed model is more suitable for price series forecasting compared to other models. And Figure 3 shows the prediction results for the hybrid model compared with the actual series and single model.

Table 3: Comparison criteria related to proposed models.

Models	Index
	MSE
SVR	0.001323
MODWT-ARIMA-GJR-GARCH-SVR	0.000732
RBFNN	0.002379
MODWT-ARIMA-GJR-GARCH- RBFNN	**0.000636**
ARIMA-GJR-GARCH	0.0006828

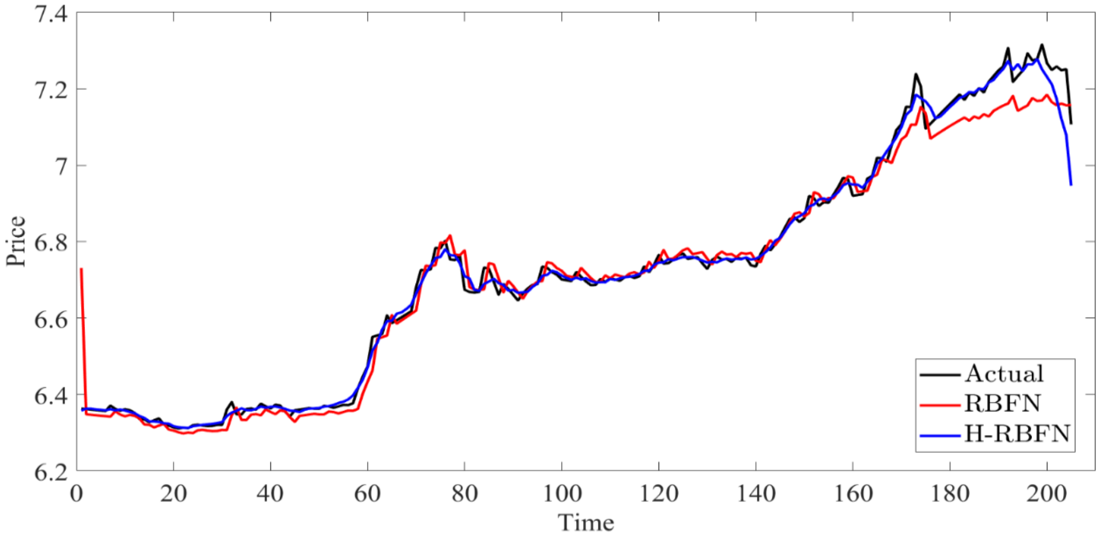

Figure 3: Prediction results

4. Conclusion:

In this study, we suggested a hybrid model based on MODWT. That is used to deconstruct the original time series into both (approximation and detailed) coefficients. The proposed model is used to model the (linear and nonlinear) components of the price series. Experimental results shown the ability of MODWT to analyze, highlight and predict important events, as it was proven that the hybrid model that uses MODWT outperforms traditional methods in modeling and forecasting financial data compared to other proposed models.

Authors Declaration:

Conflicts of Interest: None

-We Hereby Confirm That All The Figures and Tables In The Manuscript Are Mine and Ours. Besides, The Figures and Images, Which are Not Mine, Have Been Permitted Republication and Attached to The Manuscript.

- Ethical Clearance: The Research Was Approved By The Local Ethical Committee in The University.

References:

1. Ahasan, Md.Nazmul , Abdul Khalek, Md. and Alam, Md.Mesbahul. (2019). "Modeling via Wavelet GARCH Algorithm on Multivariate ENSO Index". *International Journal of Scientific and Research Publications (IJSRP),* Vol.9, No.7, pp.9195. doi:https://doi.org/10.29322/ijsrp.9.07.2019.p9195.

2. Al Rababa'A, A.R. (2017). Uncovering Hidden Information and Relations in Time Series Data with Wavelet analysis: Three Case Studies in Finance. PhD thesis. University of Stirling Scotland, United Kingdom..

3. ALhameed, A. (2020). Price Efficiency and the Forecasting of Financial Market Index Using Econometric Models and Artificial Neural Networks (A Comparative Study of Damascus Stock Exchange and Some Arab Financial Markets). PhD thesis, University of Hama, Hama.

4. ALSHAMMARI, T.S., ISMAIL, M.T., AL-WADI, S., SALEH, M.H. and JABER, J.J. (2020). "Modeling and Forecasting Saudi Stock Market Volatility Using Wavelet Methods". The Journal of Asian Finance, Economics and Business, Vol.7, No.11, pp.83-93. doi:https://doi.org/10.13106/jafeb.

5. Amirian, M. and Schwenker, F. (2020). "Radial Basis Function Networks for Convolutional Neural Networks to Learn Similarity Distance Metric and Improve Interpretability". *IEEE Access*, Vol. 8, pp.123087–123097. doi:https://doi.org/10.1109/access.2020.3007337.

6. Andersson, O. and Haglund, E. (2014). "Financial Econometrics: A Comparison of GARCH type Model Performances when Forecasting VaR". Bachelor of Science Thesis Fall 2014, Department of Statistics, Uppsala University.

7. Anjoy, P. and Kumar Paul, R. (2017). "Wavelet Based Hybrid Approach for Forecasting Volatile Potato Price". Journal of the Indian Society of Agricultural Statistics, [online] Vol.71, No.1, pp. 7–14. Available at: www.isas.org.in/jisas [Accessed 2017].

8. Chandar, S., Sumathi, M. and Sivanandam, S.N. (2016). "Prediction of Stock Market Price using Hybrid of Wavelet Transform and Artificial Neural Network. Indian Journal of Science and Technology".Vol.9, No.8. doi:https://doi.org/10.17485/ijst/2016/v9i8/87905.

9. Chang, W.-Y. (2013). "An RBF Neural Network Combined with OLS Algorithm and Genetic Algorithm for Short-Term Wind Power Forecasting. Journal of Applied Mathematics".Vol.1, No.3, pp. 1–9. doi:https://doi.org/10.1155/2013/971389.

10. Chen, G., Wang, D., Zhao, S. and Fu, S. (2016). "Research on GA-RBF Optimization Algorithm in the Prediction of Yield Loss of Maize Diseases and Pests". 10th International Conference on Computer and Computing Technologies in Agriculture (CCTA), Dongying, China. pp. 257-267

11. Dghais, A.A.A. (2016). The Causal Relationship Between Stock Markets: A Wavelet Transform-Based Approach. Phd Thesis, University Sains Malaysia, Malaysia.
12. Edward, N. (2011). "Modelling And Forecasting Using Time Series Garch Models: An Application Of Tanzania Inflation Rate Data". M.Sc. (Mathematical Modelling) Dissertation.
13.Fan, S., Hao, D., Feng, Y., Xia, K. and Yang, W. (2021). "A Hybrid Model for Air Quality Prediction Based on Data Decomposition". Vol.12, No.5, pp.210–210. doi:https://doi.org/10.3390/info12050210.
14. Ghaeini, V.V., Kimiagari, A. mohammad and Atrabi, M.J. (2018). "Forecasting Stock Price Using Hybrid Model Based on Wavelet Transform in Tehran and New York Stock Market". International Journal of Finance and Managerial Accounting, Vol.3, No.11.
15.Gherman, M., Terebes, R. and Borda, M. (2012). "Time series analysis using wavelets and GJR-GARCH models. European Signal Processing Conference, pp.2138–2142.
16. Hidayana, R., Sukono and Napitupulu, H. (2021). "ARMA-GJR-GARCH Model for Determining Value-at-Risk and Back testing of Some Stock Returns". Proceedings of the Second Asia Pacific International Conference on Industrial Engineering and Operations Management Surakarta, Indonesia, September 14-16, 2021.
17. Hongguang, L. (2016). Multi-frequency Analysis for High Frequency Trading. PhD thesis, University of Hong Kong, Hong Kong .
18. K U, J. and C Kovoor, B. (2020). "A Wavelet-based Hybrid multi-step Wind Speed Forecasting Model Using LSTM and SVR". Wind Engineering, Vol.45, No.5, doi:https://doi.org/10.1177/0309524X20964762.
19. Kazem, B. (2016). Forecasting the use of generalized autoregressive conditional heteroscedastic models (GARCH) seasonality with practical application. MA. thesis, University of Baghdad, Baghdad.
20. Kia, A. (2012). "Using MLP and RBF Neural Networks to Improve the Prediction of Exchange Rate Time Series with ARIMA". International Journal of Information and Electronics Engineering. doi:https://doi.org/10.7763/ijiee.2012.v2.157.
21. Kumar, A. and K. Joshi, L. (2011). "MODWT Based Time Scale Decomposition Analysis of BSE and NSE Indexes Financial Time Series". *Int.* Journal of Math. Analysis, Vol. 5, No.27, pp.1343 - 1352.
22. Kumar, V., Singh, N., "Deepak Kumar Singh and Mohanty, S.R. (2017). Short-Term Electricity Price Forecasting Using Hybrid SARIMA and GJR-GARCH Model". Lecture notes on data engineering and communications technologies, pp.299–310. doi:https://doi.org/10.1007/978-981-10-4585-1_25.
23. Lv, P. and Yue, L. (2011). "Short-term Wind Speed Forecasting Based on non-stationary Time Series Analysis and ARCH Model". International Conference on Multimedia Technology, Hangzhou, China pp. 2549-2553. doi:https://doi.org/10.1109/icmt.2011.6002447.
24. Masset, P. (2008). "Analysis of Financial Time-Series Using Fourier and Wavelet Methods". *SSRN Electronic Journal*. doi:https://doi.org/10.2139/ssrn.1289420.
25. Misiti, M., Misiti, Y., Oppenheim, G. and Poggi, J.-M. (2022). "Wavelet Toolbox™ 4 User's Guide". © COPYRIGHT 1997–2009 by the MathWorks, Inc.
26. Mohammed, M. and Ahmed, L. (2023). "A Proposed Wavelet and Forecasting Wind Speed with Application". Ibn Al-Haitham Journal for Pure and Applied Sciences. Vol.36, No.2.
27. Nooruldeen A. Noori and Azher A. Mohammad (2022). "Dynamical Approach in studying GJR-GARCH (Q,P) Models with Application". Tikrit Journal of Pure Science, Vol.26, No.2, pp.145–156. doi:https://doi.org/10.25130/tjps.v26i2.131.
28. Okasha, M. and Yaseen, A. (2016). "Comparison between ARIMA Models and Artificial Neural Networks in Forecasting Al-Quds Indices of Palestine Stock Exchange Market". doi:https://www.researchgate.net/publication/258221036.

29. Pahlavani, M. and Roshan, R. (2015). "The Comparison among ARIMA and Hybrid ARIMA-GARCH Models in Forecasting the Exchange Rate of Iran". International Journal of Business and Development Studies, Vol. 7, No.1.
30. Pandey, T., Jagadev, A., Dehuri, S. and Bae Cho, S. (2020). "A novel committee machine and reviews of neural network and statistical models for currency exchange rate prediction: An experimental analysis". Journal of King Saud University - Computer and Information Sciences, Vol.32, No.9, pp.987–999. doi:https://doi.org/10.1016/j.jksuci.2018.02.010.
31. Paul , Dr.R., Bhar, Dr.L.M. and Paul, Dr.A.K. (2020). "Study of Long Memory and Periodicities in Climate Variables in Different Meteorological Subdivisions of India". ICAR-Indian Agricultural Statistics Research Institute Library Avenue, PUSA, New Delhi–110 012 www.iasri.res.in, p.104. doi:https://doi.org/www.iasri.res.in.
32. Pourghorban, M. and Mamipour, S. (2020). "Modeling and forecasting the electricity price in iran using wavelet-based GARCH model. Iranian Journal of economic studies", Vol.9, No.1, pp.233-260. doi:https://doi.org/10.22099/ijes.2021.38026.691.
33. Que, Q. and Belkin, M. (2016). "Back to the Future: Radial Basis Function Networks Revisited. International Conference on Artificial Intelligence and Statistics, pp.1375–1383.
34. Rashedi, K.A., M Taufik Ismail, S. Al Wadi and Abdeslam Serroukh . (2020). "Outlier Detection Based on Discrete Wavelet Transform with Application to Saudi Stock Market Closed Price Series". The Journal of Asian finance, economics and business, Vol.7, No.12, pp.1–10. doi:https://doi.org/10.13106/jafeb.2020.vol7.no12.001.
35. Sehgal, V., Tiwari, M.K. and Chatterjee, C. (2014). "Wavelet Bootstrap Multiple Linear Regression Based Hybrid Modeling for Daily River Discharge Forecasting". Water Resources Management, Vol.28, No.10, pp.2793–2811. doi:https://doi.org/10.1007/s11269-014-0638-7.
36. Sharifi, M. and Abyaneh, R. (2014). "Using the Multistage RBF Neural Network in order to Predict the Deposits of Eghtesad Novin Bank and Comparing this Method with other Methods". Journal of Basic and Applied Scientific Research www.textroad.com, J. Basic. Appl. Sci. Res., Vol.4, No.3, pp.62-71.
37.Uddin, G.S., Yahya, M., Bekiros, S., Jayasekera, R. and Kling, G. (2021). "Systematic risk in the biopharmaceutical sector: a multiscale approach". Annals of Operations Research. doi:https://doi.org/10.1007/s10479-021-04402-8.
38. Vaghasia, S. (2018). An Approach Of Traffic Flow Prediction Using ARIMA Model With Fuzzy Wavelet Transform. MA.thesis, University of Windsor, Windsor.
39. Vaičiūnaitė, R., 2021. Forecasting nonstationary and nearly nonstationary time series using machine learning methods (Doctoral dissertation, Vilniaus universitetas).
40. Wang, C., Zheng, C., Lyu, X. and Xue, Y. (2019). "A Hybrid Model for Ride-hailing Service Demand Forecasting*". CCIOT 2019*: Proceedings of the 2019 4th International Conference on Cloud Computing and Internet of Things ER - . doi:https://doi.org/10.1145/3361821.3361828.
41. Wang, D., Meng, Y., Chen, S., Xie, C. and Zhao, L. (2021). "A Hybrid Model for Vessel Traffic Flow Prediction Based on Wavelet and Prophet". Journal of Marine Science and Engineering, Vol.9 No.11, pp.1231–1231. doi:https://doi.org/10.3390/jmse9111231.
42. Wang, W. and Jing, D. (2003). "Wavelet Network Model and Its Application to the Prediction of Hydrology". Article in nature and science of sleep, January, Vol.1, No.1, pp.67–71.
43. Ye, T. (2017). "Stock forecasting method based on wavelet analysis and ARIMA-SVR model". [Online] IEEE Xplore. doi:https://doi.org/10.1109/INFOMAN.2017.7950355.
44. Yu, B. and He, X.Q. (2007). "Training Radial Basis Function Networks with Differential Evolution". Zenodo (CERN European Organization for Nuclear Research). doi:https://doi.org/10.5281/zenodo.1332416.

45. Yu, L., Lai, K.K. and Wang, S. (2008). "Multistage RBF neural network ensemble learning for exchange rates forecasting. Neurocomputing", Vol.71, No.16-18, pp.3295–3302. doi:https://doi.org/10.1016/j.neucom.2008.04.029.
46. Zainudin, N., Mohamed, N., Aleng, N. and Rusmili, S. (2015). "Application Of Radial Basis Function Network On Parkinson Data". Journal Teknologi (Sciences & Engineering), Vol. 77, No.33, pp.95–103.
47. Zeng, Z. and Khushi, M. (n.d.). "Wavelet Denoising and Attention-based RNN-ARIMA Model to predict Forex Price". *IJCNN 2020*. doi:https://doi.org/10.48550/arXiv.2008.06841.
48. Zhiping, L. (2009). "Analysis of Stationary and non-stationary Long Memory Processes : estimation, Applications and Forecast". [Online] Available at: Zhiping Lu. Analysis of stationary and non-stationary long memory processes: estimation, applications and forecast. Mathematics [math]. École normale supérieure de Cachan - ENS Cachan, 2009. English. fftel-00422376.

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أنموذج هجين للتنبؤ المالي يستند على التحويل المويجي المنفصل الأقصى المتداخل؛ دليل من أسعار الصرف الصينية

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مستخلص البحث:
في بعض السلاسل الزمنية ، وخاصة المالية تحدث التكرارات المنخفضة والمرتفعة في نطاق زمني قصير أو لفترة محددة ، تحدث الظواهر بحيث لا يمكن مشاهدتها في بقية السلسلة الزمنية، في هذه الحالة يمكن ان يكون تجزئة السلسلة الزمنية الى سلاسل تأسيسية مفيد جداً، وذلك السلسلة الزمنية الى معلومات منخفضة وعالية التردد مما يسمح بالكشف عن الاتجاهات و لما يتمتع به التحويل المويجي من امكانية تجزئة الانهيار والانقطاعات في البيانات التي قد تُفقد عند استخدام طرق التحليل الاخرى. للتعامل مع التنبؤات بالسلاسل الزمنية غير المستقرة وبهدف تحسين دقة التنبؤ بنمط التقلبات في أسعار الصرف، نستخدم تحويل المويجات مع منهجية التهجين لبناء نموذج هجين يدمج بين (GJR-GARCH ونموذج ARMA) ونموذج الانحدار الذاتي والمتوسط المتحرك ((MODWT التحويل المويجي الاقصى المتداخل الزمنية المالية، من خلال بحيث يكون قادراً على التقاط التقلبات في السلاسل RBFNN) ونموذج الشبكة العصبية ذات الاساس الشعاعي (من خلال تطبيقها على سعر صرف اليوان الصيني، توفر تقنية تحويل المويجات ميزة مفيدة تعتمد على تحليل البيانات مما يحسن من اداء نموذج التنبؤ. تم تحليل سلسلة اسعار الصرف إلى معاملاتها (التقريبية والتفصيلية) الى ثلاثة مستويات بإستخدام التحويل المويجي من. أظهرت النتائج التجريبية لهذه الدراسة أنَ النموذج المقترح يتمتع بدقة تنبؤية أعلى من النموذج المنفرد والنماذج MODWT) النوع الهجينة الاخرى.

نوع البحث: ورقة بحثية.
المصطلحات الرئيسة للبحث: التحويل المويجي الاقصى المتداخل ، الشبكة العصبية ذات دالة الاساس الشعاعي، نموذج الانحدار الذاتي والمتوسط المتحرك، نموذج GJR- GARCH