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Analysing the Dependency of Exchange Rate on Crude oil Price with Wavelet Networks: Evidence from India

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ABSTRACT

The crude oil prices as well as the effective exchange rate of the dollar are both time series and non-stationary as well. In this paper, we investigate the relationship between real effective exchange rate and crude oil prices by hybrid wavelet network. We use a simple Multi-layer Perceptron Neural Network (MLPNN) based wavelet decomposition to analyse the relationship between real effective exchange rate and crude oil prices. The study for India indicate that crude oil prices effect the real effective exchange rate and the hybrid model better untangle the relationship between real effective exchange rate and crude oil than other models.

Keywords:- *E*xchange rate, crude oil prices, neural networks, wavelets, wavelet networks.

I. INTRODUCTION

Exchange rate is one of the most important determinants of country's relative level of economic health. Exchange rates play a vital role in country's level of trade, which is critical for every free market economy in the world. For this reason, exchange rates are among the most watched analyzed and government manipulated economic measures [1]. This relationship between the crude oil price and the US dollar exchange rate has attracted the interest of many economists. The crude oil prices as well as the effective exchange rate of the dollar are both time series and are non-stationary as well.

There is the inverse relationship between the US dollar exchange rate and the Brent crude oil price. He adds oil prices to the basic monetary model of exchange rate determination and directly estimated an equation of the Brent oil price that contains other relevant variables in addition to the nominal effective exchange rate of the US dollar in the period from 1994 to 2010 [16]. A study by [23] explored the linear and non-linear Granger casualties between oil price and the real effective exchange rate of the Indian currency by a wavelet based analysis and suggested that there are linear and nonlinear casual relationships between the oil price and the real effective exchange rate of India at higher time scales. A study by [24] examined the dynamic relationship between oil prices and exchange rate of selected emerging economies. It contributes to the literature in at least three points, first contrary to the general use of developed economies, the author opted emerging markets to study the relationship between oil prices and exchange rates. Second, un-parallel to the literature using monetary models to explore the exchange rates with low frequency data, oil is taken as alternative asset class and use daily oil price data to investigate the dynamics of exchange rate of an emerging market. Third, this paper shows how this relation has changed by comparing the relationship before and after the financial crisis. The study used exchange rates of 13 emerging countries during 2003-10.The study used 5 day week daily time series data for the period 01-03-2003 to 06-02-2010. The description of the movements of exchange rate and oil price and the assertion that changes in exchange rates have impact on oil prices is indicated by the study by Bloomberg and Harris(1995). A study by [9] suggests that movements in oil prices should affect exchange rates.

In this study we examine the relationship between real effective exchange rate and crude oil prices by using the Hybrid Wavelet and Multilayer Perceptron Neural network (MLPNN) model. We observe that using wavelets for decompositions turn out to be useful in unveiling the relationship between these two time-series and this hybrid model performs better than other models in forecasting real effective exchange rate by crude oil prices.

II. WAVELETS

Wavelets theory is based on Fourier analysis, in which any function can be represented as the sum of sine and cosine functions. A wavelet $\psi(t)$ is simply a function of time t that obeys a basic rule, known as the wavelet admissibility condition[8]:

$$C_{\psi} = \int_0^{\infty} \frac{|\psi(f)|}{f} df < \infty \quad \text{---------- (1)}$$

where ψ(f)is the Fourier transform, a function of frequency f, of ψ(t). Depending on normalization rules, there are two types of wavelets within a given function/family where **(2a)** represents father wavelet and **(2b)** represents mother wavelet with j =1,……, *J*and *J*-level wavelet decomposition [18]:

$$\phi_{j,k} = 2^{-j/2}\phi\left(t - 2^j k / 2^j\right) \quad \text{--- (2a)}$$

$$\psi_{j,k} = 2^{-j/2}\psi\left(t - 2^j k / 2^j\right) \quad \text{---- (2b)}$$

Based on the length of data there are two types of wavelet transforms namely continuous wavelet transform (CWT) and discrete wavelet transform (DWT). Since most of the time series have finite number of values, discrete version of wavelet transform is used in finance and economics applications and in most of the natural sciences. Discrete wavelets are defined as[13]**:**

$$\phi_{j,k} = 2^{j/2}\phi\left(2^j t - k\right) \quad \text{---------- (3a)}$$

$$\psi_{j,k} = 2^{j/2}\psi\left(2^j t - k\right) \quad \text{----------- (3b)}$$

Where ϕ and ψ satisfying as follows:

$$\phi(t) = \sum_k h(k)\phi_{1,k} \quad \text{------ (4a)}$$

$$\psi(t) = \sqrt{2}\sum_k (-1)^k h(-k+1)\phi(2t-k) = \sqrt{2}\sum_k g(k)\phi(2t-k) \quad \text{------- (4b)}$$

In practice the DWT is implemented via pyramid algorithm. For each iteration of pyramid algorithm three objects are required as the data vector x, the wavelet filter h_i and the scaling filter g_i. At the first level, j =1, DWT wavelet coefficients $\psi_{i,t}$ and scaling coefficients $v_{i,t}$ as follows:

$$v_{l,t} = \sum_{l=0}^{L-1} g_l x_{2t+1-l \bmod N} \quad \text{---- (5a)}$$

$$\psi_{l,t} = \sum_{l=0}^{L-1} h_l x_{2t+1-l \bmod N} \quad \text{---- (5b)}$$

Wavelet analysis has shown a tremendous performance in the area of financial time series analysis as it provides an important tool for extracting information from financial data with applications ranging from short term prediction to the testing of market models due to its flexibility to handle very irregular data series. Wavelets possess ability to locate precisely time regime shifts and discontinuities by decomposing financial time series on a variety of time scales simultaneously so that relationships between economic variables may well differ across time scales. They have been successfully used in forecasting stock market prices, crude oil prices, GDP growth, trading prices, exchange rates, expenditure and income, money growth and inflation, volatility in foreign exchange markets, price fluctuations, sales etc from the last decade([12],[17],[19][26],[28] and [31]).

III. ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN), originally developed to mimic basic biological neural systems- the human brain particularly, are composed of a number of interconnected simple processing elements called neurons or nodes .Each node receives an input signal which is the total "information" from other nodes or external stimuli, processes it locally through an activation or transfer function and produces a transformed output signal to the other nodes or external outputs. Although each individual neuron implements its function rather slowly and imperfectly, collectively a network can perform a surprising number of tasks. This information processing characteristic makes ANNs a powerful computational device and able to learn from examples and then to generalize to examples never seen before.

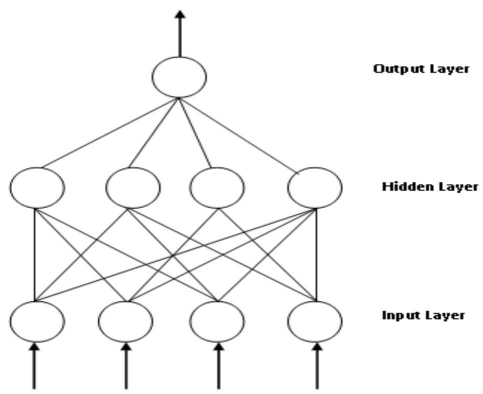


Figure 1. A typical MLP Neural network.

Different ANN models have been proposed during the last two decades. In this study we use Multi-layer

Perceptron (MLP) model which is composed of several layers nodes. Fig. 1. depicts the fully connected MLP model with one hidden layer. The first or the lowest layer is an input layer where the external information is received. The last or the highest layer is an output layer where the problem solution is obtained. These two layers are separated by one or more intermediate nodes called the hidden layer. The nodes in adjacent layers adjacent are usually connected by acyclic arcs from a lower layer to a higher layer ([5] and [34]).

ANNs have drawn considerable attention in financial engineering in the recent years because of their interesting learning abilities. Recent studies have revealed the predictive power of the ANNs in approximating discontinuous functions as they have the ability to formalize unclassified information and more importantly, to forecast financial time series. Another important advantage of ANN is that they can approximate any nonlinear function without having any prior assumption about the properties of the data series unlike the traditional forecasting methods which assumes a linear relationship between inputs and outputs. In recent years, AAN have successfully been applied for the forecasting of financial time series such as stock market indexes, exchange rates, crude oil prices, inflation and gold prices([3],[7],[10],[15],[22][25],[27]and [35]).

IV. WAVELET NEURAL NETWORKS

The origin of wavelet networks can be traced back to the work of Daugman in 1988, which uses Gabor wavelet and neural network for the classification of images and became popular after the pioneer work of Zhang, Benveniste and Szu in early 1990's. Wavelet neural networks are suitable for forecasting the financial time series because wavelets can decompose the financial time series into their time-scale components and unravel the non-linear relationship between economic variables. In recent years, economists have shown a considerable interest for forecasting financial time series using hybrid models.

Wavelet neural network have been widely-used for forecasting oil prices[28], stock index[6], electricity demand[31]and other time series. [21] is an example, in this study; the author proposes a hybrid model which combines Wavelet Neural Network and Genetic Algorithm for forecasting exchange rates. The experimental results show that the proposed method provides satisfactory performance for different forecasting horizons and, strangely the author claims that the accuracy of forecasting does not decline when the forecasting horizon increases. The result of empirical study shows that Wavelet Neural Network model give better results for time series forecasting than other models. The comparison study of forecast accuracy show that the first procedure (with stepwise) of non-stationary time series yields the best forecast compared to ARIMA, MAR and WNN models by using other procedures. It's showed by the smallest RMSE at testing data[20].

The back-propagation neural network (BPNN) model and the wavelet neural network (WNN) model were compared by the crisis forecasting accuracy and in-sample and out-of-sample test. The results showed that WNN model could be applied to the currency crises could effectively capture the economic variables associated with the currency crises, and might be to provide a more powerful tool for macroeconomic time series data [29]. A method based on the wavelet analysis and the artificial intelligence was used to predict the A300 index in China and NASDAQ index in the USA. Comparing with wavelet-ARIMA model and simple BP neural network, the combined model of wavelet and neural network demonstrate superiority in predicting power [4]. An integrated system is presented in [11] where wavelet transforms and recurrent neural network (RNN) based on artificial bee colony (abc) algorithm (called ABC-RNN) are combined for stock price forecasting. The study was based on the simulation results of several international stock markets, including the Dow Jones Industrial Average Index (DJIA), London FTSE-100 Index (FTSE), Tokyo Nikkei-225 Index (Nikkei), and Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and demonstrated that proposed hybrid system was highly promising and could be implemented in a real-time trading system for forecasting stock prices and maximizing profits. A methodology that combines artificial intelligence modeling techniques with wavelet multiresolution methodology for forecasting of daily spot foreign exchange rates of major internationally traded currencies is proposed in [14]. Results of the empirical study indicate superior performance of the proposed technique as compared to the traditional exchange rate forecasting models.

The traditional prediction model is not able to achieve a satisfying prediction effect in the problem of a nonlinear system and non-stationary financial signal. The wavelet neural network has overcome the deficiency of traditional prediction model which is limited to linear system when predicting. The returns in Shanghai stock market from January 10th, 2006 to July 18th, 2008 was used to compare simulation error of stock market returns between BP network and wavelet neural network. The results show that the simulation result of wavelet neural network is more accurate than that of BP network, and wavelet neural network constructed can forecast stock market returns more accurately [30].

V. EMPIRICAL STUDY

A. Datasets and Forecasting Criteria

The time series data constitutes of monthly values from April, 1993 to February, 2015 for real effective exchange rate and crude oil prices. The values are obtained from the official website of Reserve Bank of India for real effective exchange rate (REXR) and from the website of U.S. Energy Information Administration (EIA) for West Texas Intermediate (WTI) - Cushing, Oklahoma for spot prices for crude oil. The descriptive statistics for both the time series in natural logarithms (levels) and log first difference (returns) form is presented in Table 1 and depicted in Fig.1 for returns for both the time series. A preliminary investigation of descriptive statistics indicates that the sample means of both time series is positive in levels and returns form. The oil returns and level form of real effective exchange rate is negatively skewed as indicated by their measure of skewness.The data series in level for real effective exchange rate demonstrate excess kurtosis which indicates that the distribution is leptokurtic relative to normal distribution. Jarque-Bera normality test rejects normality of all series at 1% level of significance except for data series in level for real effective exchange rate. The Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test is used assesses the whether the time series is trend stationary or not. It is observed that the KPSS test rejects the stationarity of oil and real effective exchange rate levels while accepts the stationarity of oil and real effective exchange rate returns.

	Log Oil	Returns OIL	Log REXR	Returns REXR
Mean	1.605	0.002	1.641	0.001
Median	1.560	0.006	1.651	0.000
Maximum	2.127	0.089	1.823	0.037
Minimum	1.055	-0.144	1.496	-0.030
Std.Dev	0.297	0.036	0.077	0.009
Skewness	0.027	-0.780	-0.197	0.524
Kurtosis	-1.467	1.801	-0.158	3.760
Jarque-Bera	23.295	59.507	2.073	158.671
KPSS	1.3617	0.1216	2.8063	0.1054

Table 1: Descriptive Statistics

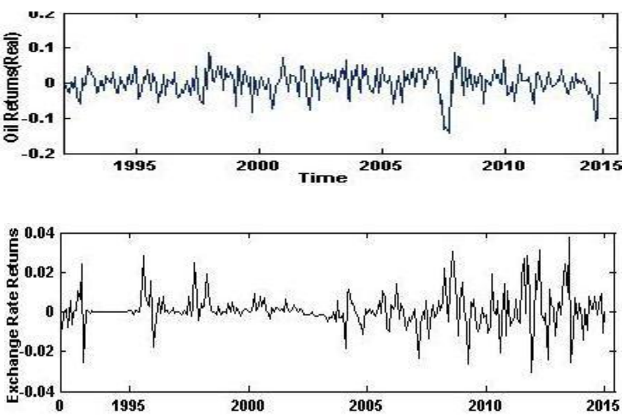


Fig.1: Exchange Rate and Crude oil Returns

In this study, the forecasting performance of hybrid wavelet and neural network model is compared with individual ANN and wavelet based model. The performance measures are root mean square error (RMSE), mean absolute percentage error (MAPE) defined as:

$$RMSE, R = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

Where X_{obs} is observed value and X_{model} is forecasted value at time/place i.

MAPE,

$$\mathrm{M} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|,$$

where A_t is the actual value and F_t is the forecasted value.The smaller values of RMSE and MAPE, closer the predicted time series values to that of the actual value.

B. Methodology and Forecasting Results

The forecasting results of four models i.e., linear, AAN, Wavelet and hybrid model are shown in Table 3.For study with ANN, a simple Multi-layer Perceptron Neural Network (MLPNN) model is used in which the input and output layers contains one neuron to process the values of real effective exchange rate returns and observed crude oil price returns respectively. The model was trained in a process called supervised learning. In supervised learning, the input and output are repeatedly fed into the neural network. With each presentation of input data, the model output is matched with the given target output and an error is calculated. This error is back propagated through the network to adjust the weights with the goal of minimizing the error and achieving simulation closer and closer to the desired target output. The Levenberg–Marquardt algorithm (LMA) is used in the current study to train the network because of its simplicity. It is an iterative algorithm that locates the minimum function value which is expressed as sum of squares of nonlinear functions. The optimum number of neurons in the single hidden layer is determined using trial and error procedure. The model is trained up to maximum of 1000 epochs reached. Sigmoid function was used for the neurons of the hidden and output layers to process their respective inputs for the simple MLPNN model. The training of the network was considered to be completed when the network performance determined by the validation/testing was satisfactory. The network was re-trained, if it failed to perform satisfactory during testing phase. The model is trained using 263 sample monthly values from April, 1993 to February, 2015. The sample values were distributed randomly and it was observed that the model unarguably performed optimally under conditions when the samples were divided for Training (65%), Validation (10%) and Testing (25 %). Neural Network GUI toolbox of Matlab software was used for this purpose.

For wavelet based study Discrete Wavelet Transform (DWT) is used. DWT is a well-established noise removal and denoising technique and has been widely used in the financial time series analysis in the last two decades. Using wavelets to remove noise from a signal requires identifying which component or components contain the noise and then reconstructing the signal without those components. The Wavelet GUI Toolbox of Matlab software was used for this purpose that includes automatic thresholding.The de-noising procedure proceeds in three steps:

1. Decomposition by any wavelet. In our case Daubechies wavelet is used.
2. Thresholding detail coefficients. Daubechies wavelet from level from 1 to 4 and scale 4 is applied in our case, fixed form threshold was chosen and soft thresholding was applied to detail coefficients since better results are obtained when the scale is set to 4 in our case. The performance of this wavelet is depicted in Table 2.
3. Reconstruction. In our case the reconstructed series from level 1 to 4 and scale 4 (in each case) are returns of real effective exchange rate and crude oil prices. The original series and their approximations by Daubechies wavelet at scale 4 are depicted in Fig. 3. The better results are obtained at level 4.

In the Hybrid wavelet neural network model, the same wavelet decomposed (Daubechies at level 4 and scale 4) and reconstructed series of real effective exchange rate and crude oil price returns are fed to the same MLPPN model discussed earlier for ANN and the observations are recorded for the forecasted values of real effective exchange rate returns .The framework of the hybrid model is depicted in Fig 2.The results obtained in Table 3 reveals that the hybrid model outperforms the all the other three models since smaller values of RMSE and MAPE are observed in this case. This study further reestablishes the fact that real effective exchange rate is related to crude oil prices. The negative values are obtained for Standardized Coefficient 'Beta' in each case suggests that real effective exchange rate is negatively associated/correlated with crude oil prices. There is significant increase in the values of Correlation Coefficient R from linear to hybrid model which suggested that the hybrid model better unravels the relationship between the two time series. The results are depicted graphically in Fig. 4.

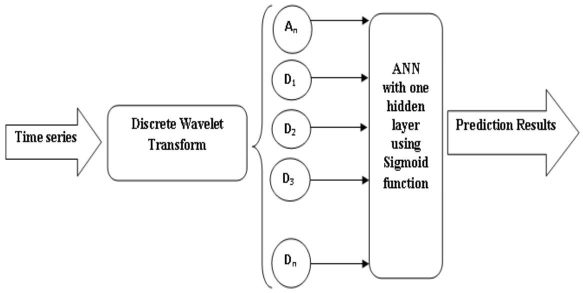


Fig 2. Framework of our Hybrid Model

Model	R	R^2	Adjusted R^2	Standardized Coefficient Beta	RMSE
Db1	.422	.178	.175	-0.422	.00978
Db2	.222	.049	.046	-0.222	.0096
Db3	.199	.040	.036	-0.199	.00911
Db4	.659	.434	.432	-0.659	.00800

Table 2: Wavelet Based Study by Daubechies

Model	R	R^2	Adjusted R^2	Standardized Coefficient Beta	RMSE	MAPE
1. Linear	.127	.016	.012	-0.127	.03547	2.75
2. ANN	.278	.077	.074	-0.278	.01036	1.48
3. Wavelet	.659	.434	.432	-0.659	.00800	1.24
4. Hybrid	.775	0.601	.599	-0.775	.00172	1.19

Table 3: Comparison of Models

VI. CONCLUSION

In this paper, we investigate the relationship between real effective exchange rate and crude oil prices by hybrid wavelet network in India over a period April, 1993 - February, 2015. We use MLPPN based wavelet decomposition to analyse the relationship between real effective exchange rate and crude oil prices. The main findings for India indicate that crude oil prices effect the real effective exchange rate. The hybrid model better runravels the relationship between real effective exchange rate and crude oil prices than ANN or Wavelet based study. The crude oil price is a reliable predictor of real effective exchange rate and provides good forecasts and this fact is established by earlier study also.

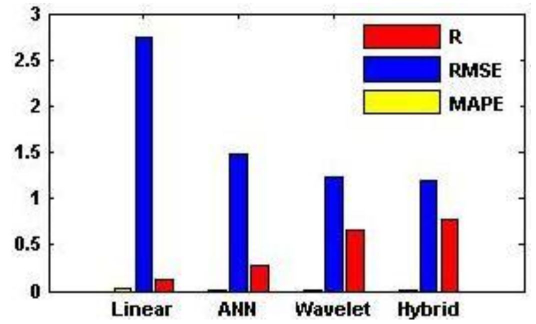
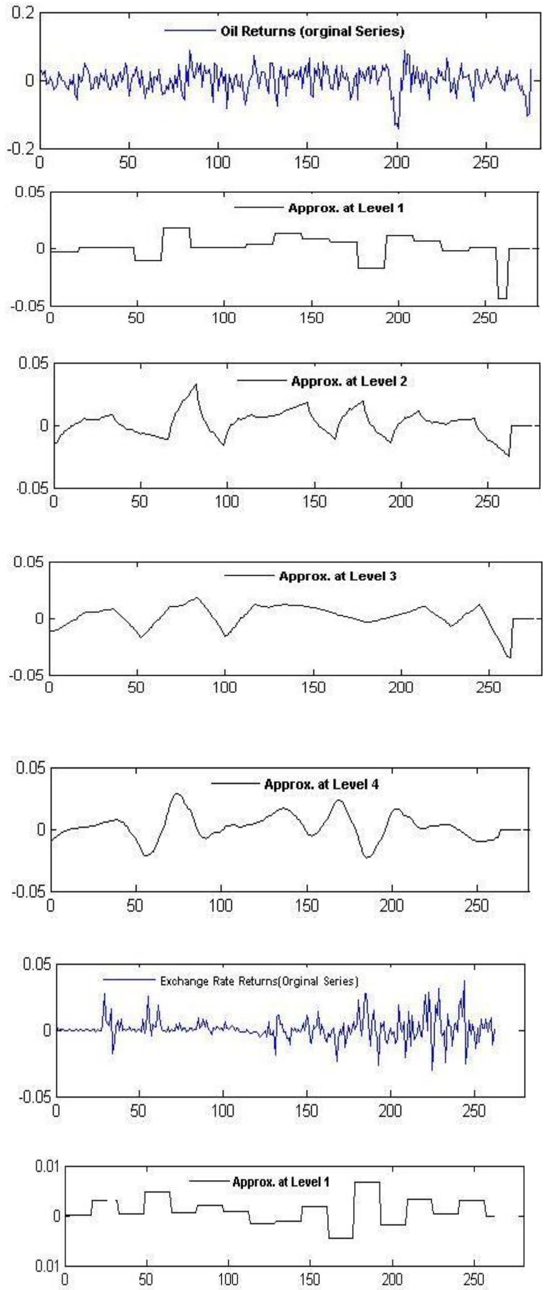


Fig 4: Comparison of Performance Measures



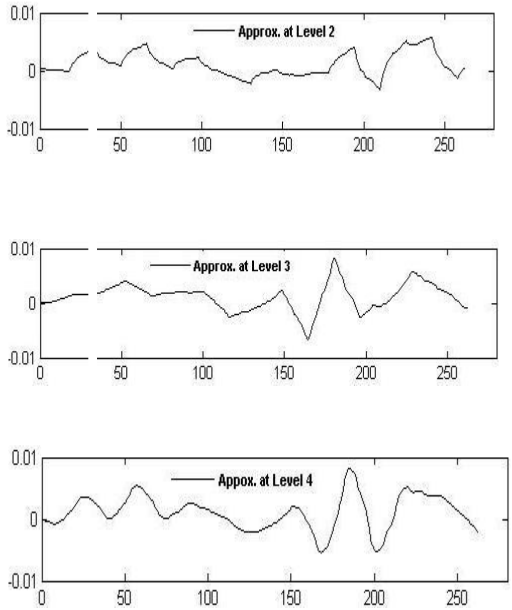


Fig. 3: Orginal Time Series and Approximations by Daubechies wavelet at scale 4.

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