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# Forecasting the Term Structure of Crude OilFuture Prices with Dynamic Neural Networks

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***Abstract***
*This study offers a multilayer feed for ward neural network model for predicting the direction of the price of crude oil over the next 20 days. In order to account for the time element, we employ a dynamic Nonlinear Auto Regressive model with exogenous input (NARX) as a kind of ANN after evaluating pre- processing data approaches.*
*We combine the output from the time series model to feed the NARX model, which is a feedback dynamic neural network. Utilizing information from January 1, 2002, to December 31, 2015, our NARX model is used. The training's results provide a clear picture of the dynamics affecting crude oil prices, and we can see how the predicted trend really played out.*
***Keywords: Crude oil price forecasting, Prediction models, Artificial Neural Networks, NARX***

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## I. Introduction

Crude oil is a crucial component of the world economy as one of the most strategically important resources in existence. Market participants and financial professionals both keep track of changes in the price of crude oil. Predicting the direction of crude oil prices is crucial not only for oil exporting and oil importing countries but also for reducing shocks on other energy markets in order to lessen the detrimental effects of price volatility. It is necessary to predict its price, but doing so is difficult due to the numerous factors that affect its trends and level of volatility, including unforeseen events like weather, financial speculations and shocks, fluctuations in foreign exchange rates, OPEC's oil policy, the dollar index, gold, heating oil spot price, wars, embargoes, and political events. Time series analysis is often a forecasting technique that concentrates on the past performance of the dependant variable. In many studies, the distribution of oil prices is believed to be normally distributed; however, due to a misunderstanding of the Central Limit Theorem, the deviation of oil prices from this distribution has been ignored. In actuality, the price of crude oil is not Gaussian. Due to the unpredictability, turbulence, and non-stationary internal indicators that influence crude oil prices, forecasting them using the basic method is a difficult undertaking. To assess and forecast future movements based on oil price history, time series models offer an option.

The generalised autoregressive conditional heteroskedasticity (GARCH) and autoregressive integrated moving average (ARIMA) models are the most often used models in time series forecasting, notably in the parametric estimation approach. A lagged series is used in the fundamental linear forecasting model known as ARIMA. ARIMA used to be employed in numerous time series analysis because to its efficacy and simplicity. GARCH may be used to analyse the volatility of a time series since it is based on the concept of non-consistent variance in a generic time series. Artificial neural networks (ANN) and other machine-learning techniques have recently been widely utilised in predicting research due to its adaptability to any time series data. An ANN has a large and expanding range of applications since it is not reliant on an asymptotic theory in econometrics.

Indeed, during the past several years, interest in artificial neural networks has exploded. These networks have been successfully used to solve a remarkable variety of problems in fields as diverse as finance, health, engineering, geology, and physics. In this contribution, we introduce a dynamic artificial neural network dubbed a nonlinear autoregressive model with external output (NARX), which uses a temporal component to enable a dynamic model and should increase prediction power.

The sections of this essay are as follows: section 2 provides a quick overview of the literature; section 3 outlines the technique employed; section 4 deals with the data and analysis; and section 5 provides a conclusion.

## II. Literature Review

Since the oil crisis in 1973, many studies focused on forecasting crude oil price. We present here a brief review of the key papers, surveyed on the various techniques used to forecast crude oil price: both traditional and statistical econometric models. Descriptions of static and dynamic artificial neural networks displayed in the section 4.

Amano (1987) was one of the first to use an econometric model for forecasting oil price. Through cointegration analysis, Gulen (1998) succeed to predict the WTI crude oil price. Morana (2001) useda semi-parametric approach based on GARCH to forecast Brent crude oil price on short term.In their early work, Ye et al. (2002) used a linear regression for forecasting WTI crude oil spot priceon short term by using OECD oil inventory levels and stocks. Few years later, Ye et al. (2006) included in their modelling nonlinear variables such as low and high inventory variables to the linear forecasting model.Others methods were carried out. By utilizing the error correction models, Lanza et al. (2005) worked on crude oil prices. Starting from OPEC behavior, Dees et al. (2007) modelled a linear model of the oil market to forecast both oil demand, oil supply and prices.At the same time, Moshiri et al.(2006) worked on the chaos and nonlinearity in crude oil prices. They compared ARMA (Autoregressive Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models for the daily forecasting of crude oil prices to FNN (Feedforward Neural Network) and concluded that the latest is the best candidate for modelling and forecasting.

It appears that both traditional statistical and econometric techniques are able to capture only linear process in data time series. Because the oil price is characterized by both high nonlinearity and high volatility, these models are inappropriate to forecast the oil price.Studies on the relation between spot prices and futures prices have been very experienced by many researchers. They displayed the importance of efficiency, prediction ability, lead and lags.Among them, Narayan (2007) and Agnolucci (2009) used GARCH model to predict spot and futures crude oil prices. Murat and Tokat (2009) worked on this relation. They showed the capacity of futures prices to predict spot price variations through random walk model.

More recently, Mohammadi et al. (2010) compared issues from different GARCH models in order to forecast crude oil price. In the same posture, Kang et al. (2009) tested CGARCH, FIGARCH and IGARCH models to forecast volatility of crude oil markets in order to measure the best one.

Ksaier et al. (2010) used the Hurst exponent in order to determine the existence of a long memory phenomenon in the daily oil return series (WTI), they concluded that unlike the GARCH and IGARCH models, the selected FARIMA-FIGARCH model is able to capture persistence in the volatility of crude oil price and FIGARCH model generates a best forecasting accuracy.In this contribution, we use a dynamic ANN model for crude oil price forecasting on short term. It is a nonparametric, nonlinear model. Because ANN lets the data speak for itself there is not a a priori assumption and feedforward network with nonlinear function allows to approximate any function. Shambora et al. (2007) experienced an ANN model to forecast the crude oil price. The target of the model is the predicted prices. They concluded that ANN outperforms other techniques. For the same purpose of forecasting, Yu et al. (2007) proposed a multiscale neural network to predict oil price. This model performed better than a single-scale one.

Lackes et al. (2009) experienced a layer backpropagation FNN to predict crude oil price trend on short term but also on mid-term and long term (i.e. 3 months). They concluded that prediction modelling with 5 neurons was less rich than with 2 neurons on the long term.ANN model was also tested by Haidar et al. (2009) to forecast crude oil prices on the short term (3 days). They displayed that the futures prices offer more information to the spot prices and increases forecasting ability.It appears that these empirical studies that display ANN performance have a better accuracy predictionthan the other models.

## III. Methodology

An information processing system called an artificial neural network (ANN) was created as extensions of mathematical models of human neuronal biology (Figure 1). Nodes or units make up an ANN and are connected by directed linkages. Each connection has a weight in numbers (W is the weight matrix). Be aware that the bias b in Figure 1 is there to serve as the real threshold for the activation function.

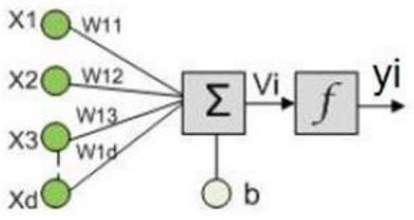



Figure 1. Mathematical model of the artificial neuron

$$v_i = \sum_{j=1}^{d} w_{ij} x_j$$

$$y_i = f(v_i) = f(\sum_{j=1}^{d} w_{ij} x_j)$$

$$w = \begin{bmatrix} w_{11}\ w_{12}\ w_{13} \dots w_{1d} \\ w_{21}\ w_{22}\ w_{23} \dots w_{2d} \\ \vdots \quad \vdots \quad \vdots \dots \vdots \\ w_{m1}\ w_{m2}\ w_{m3} \dots w_{md} \end{bmatrix}$$

Where W is the weight matrix, xj is the input neuron j, yi is the hidden neuron i's output, and f is the activation function. The weight matrix is changed when the neural networks gain new knowledge. Consequently, the overall procedure for training the network consists mostly of the following three steps:

1. Feed the input signals forward
2. Reproduce the mistake
3. Change the weights.

There are four steps involved in training the neural networks:

Data from bigger databases and other types of data sources are restricted in the first phase of the data analysis process, known as data selection. Database searches and sample methods are used at this step.

2- Data pre-processing: Data pre-processing is the coding, enrichment, and clearing of data, which entails handling missing data and adjusting for noise.

3- Data transformation: aims to change data into a format that the NN can use. 4- Neural Networks training and selection.

**Dynamic Neural Networks**

Neural networks may be divided into dynamic and static categories, as well as categories for dynamic neural networks with and without feedback. In no feedback dynamic neural networks, the output of the network is dependent on both the network's current input and its prior inputs. In feedback dynamic neural networks, the network's output is influenced by both its current input and its prior inputs, outputs, and states in addition to its current input. Time series prediction is one of the main uses of dynamic neural networks. The patterns of the process time series of the expected target are examined in time series prediction. The MATLAB Neural Networks Time Series Tools offer three categories to address three,

- Nonlinear autoregressive with external input (NARX )
- Nonlinear autoregressive (NAR)
- Nonlinear input-output

NARX, which we employ in our article, is a feedback dynamic neural network that also resembles a back-propagation neural network since it depends on the network's prior inputs and outputs. Figure 1 depicts the NARX network's organisational structure utilised in the article.

**Nonlinear Autoregressive Network with Exogenous Inputs (NARX):**

In the field of system of identification, the NARX models are frequently employed (Xie et al., 2009). All of the specific dynamic networks that have been addressed so far have either been feed-forward networks or focused networks, where the dynamics are only present at the input layer. A recurrent dynamic network with feedback links encompassing numerous network levels is the nonlinear autoregressive network with exogenous inputs (NARX). The linear ARX model, which is frequently employed in time series modelling, serves as the foundation for the NARX model.

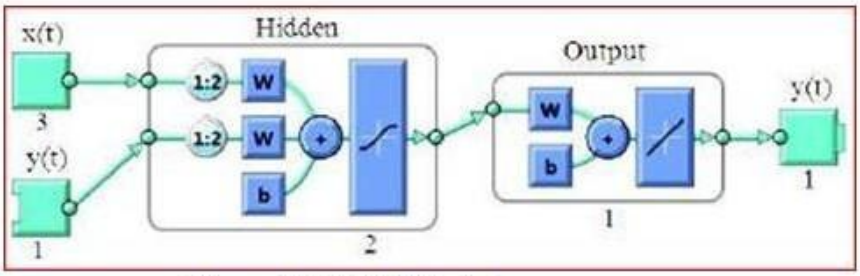



Figure 2 : NARX Model

Figure 2 shows how the typical NARX network looks. With a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer, the standard NARX network used here is a two-layer feed forward network. The previous values of the input, x(t), and output, y(t), sequences are also stored in this network using tapped delay lines (d). In order to start training with the third data point, first load the training data and utilise tapped delay lines with two delays for both the input and the output. The series-parallel network has two inputs: the x (t) sequence and the y (t) sequence. You should be aware that the y(t) sequence is regarded as a feedback signal, an input that is also an output (target). Using the model

$$y_t = f(y_{t-1},\ldots,y_{t-d}, x_{t-1},\ldots,x_{t-d})$$

where yt is the NARX network's output, as well as tapped delay lines (d) that hold the prior values of the xt and yt sequences.

## IV. Data Selection and Case study

The WTI is regarded as the benchmark for the price of crude oil internationally by the majority of governments and private sector participants in the oil industry. Changes in the WTI oil market have an impact on the price of crude oil on other markets (He K, Yu L, Lai KK 2012).Our data sample for this study includes five daily time series, including the price of crude oil, the euro/dollar exchange rate, stock prices, the yield on the US 10-year Treasury, and the volatility index, sometimes known as the "fear index," for the period from January 1, 2002, to December 31, 2015. These data sets were gathered from sources using DATASTREAM.

- US interest rate: Falling interest rates will enhance loan accessibility and boost demand for crudeoil, which will lead to an increase in oil prices.
- SP500 index: This index, which measures the health of the financial markets, is included to indicate the status of the economy in general and potential impacts on oil prices. Several earlier research have found a significant correlation between crude oil prices and stock markets.
- Euro-Dollar Exchange Rate: The Euro-Dollar Exchange Rate is referred to as a factor that affects daily changes in crude oil prices. Crude oil prices and the Euro-Dollar Exchange Rate are negatively correlated; a stronger U.S. Dollar results in lower crude oil prices, and a weaker U.S. Dollar results in higher crude oil prices (see graph below).


Fig. 1: daily evolution

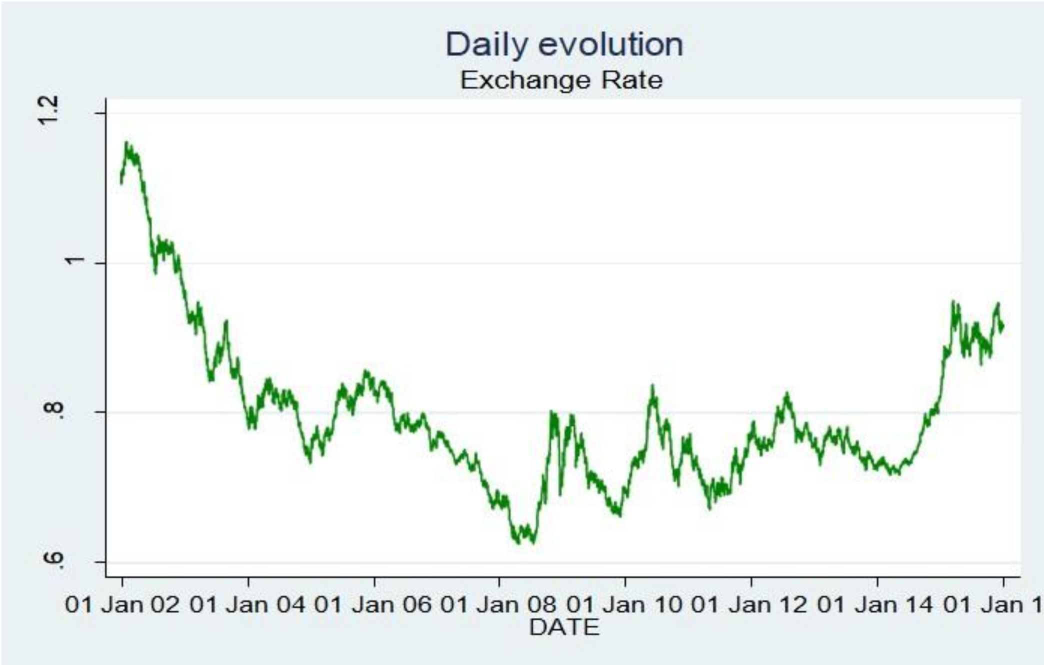



Fig. 2: daily evolution exchange rate

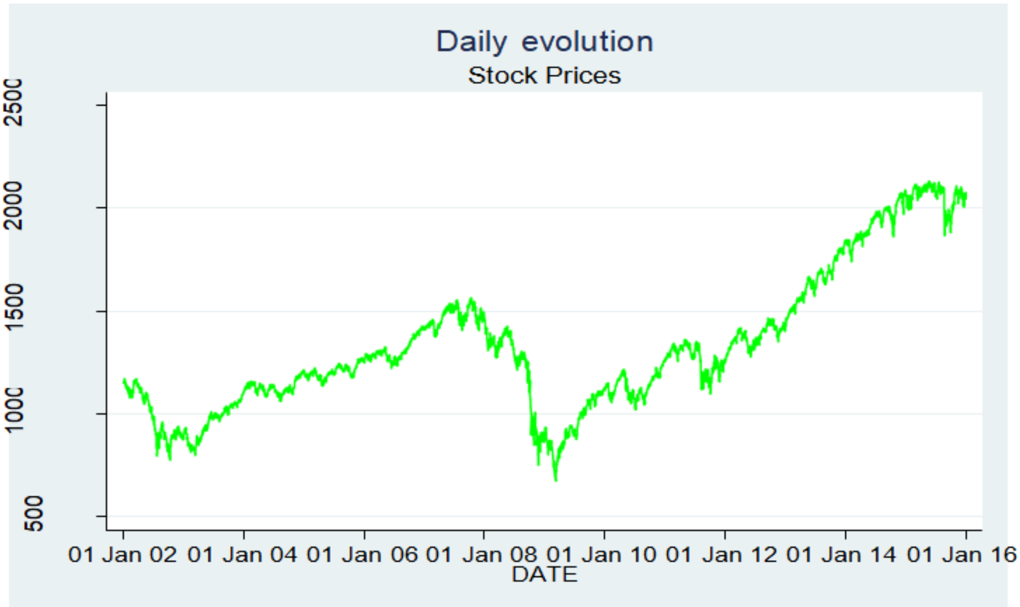



Fig. 3: daily evolution stock prices

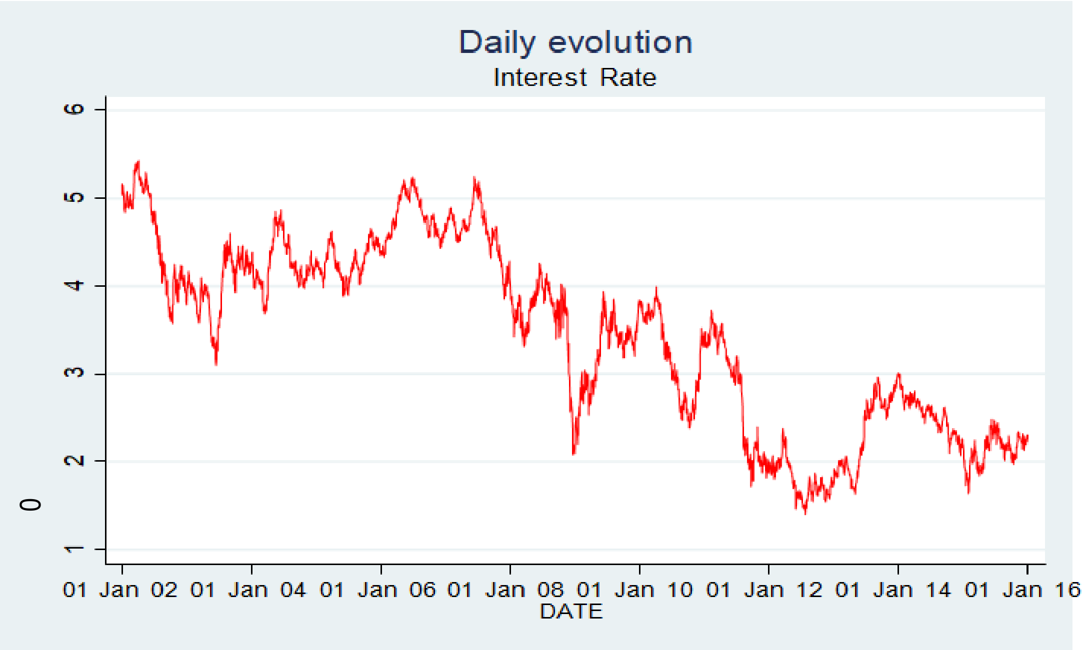



Fig. 4 : daily evolution interest rate

**Analysis Model**

In this contribution, a nonlinear autoregressive with exogenous input (NARX) model (Figure 3) is used to forecast future values of a time series, y (t), based on historical values of the time series in question and historical values from other time series, xi (t). In these studies, we employed two-layer feed-forward networks with hyperbolic tangent transfer functions in the hidden layer and linear transfer functions in the output layer to conduct NARX with various numbers of hidden layers, tapping delay lines (d), and one output neuron.When generalisation increases, as shown by a rise in the Mean Square Error (MSE) of the validation samples, training automatically terminates.

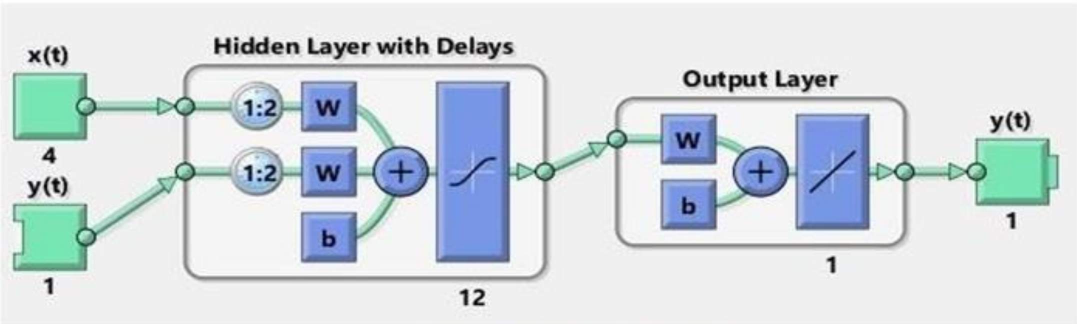



Figure 3: NARX Model used

In Figure 4, all R values during the neural network's training are more than 0.998. This demonstrates that the neural network model's output closely resembles the target and that the model is suitable.

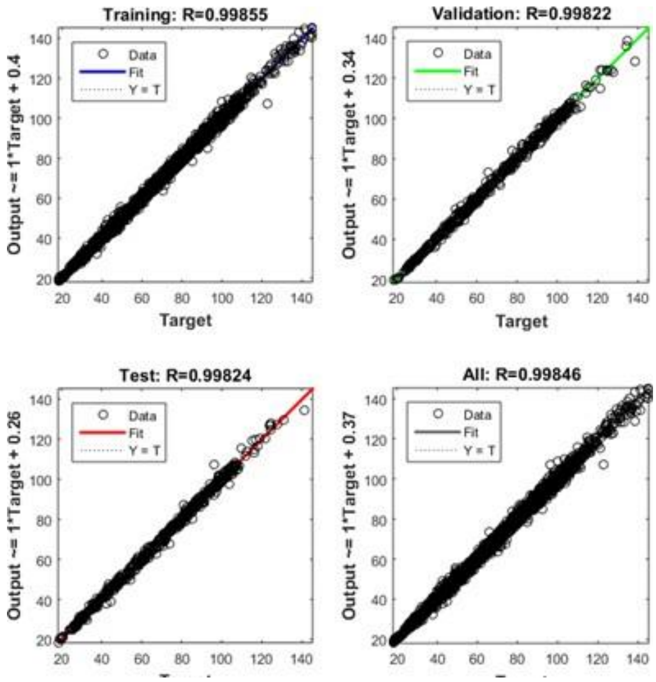
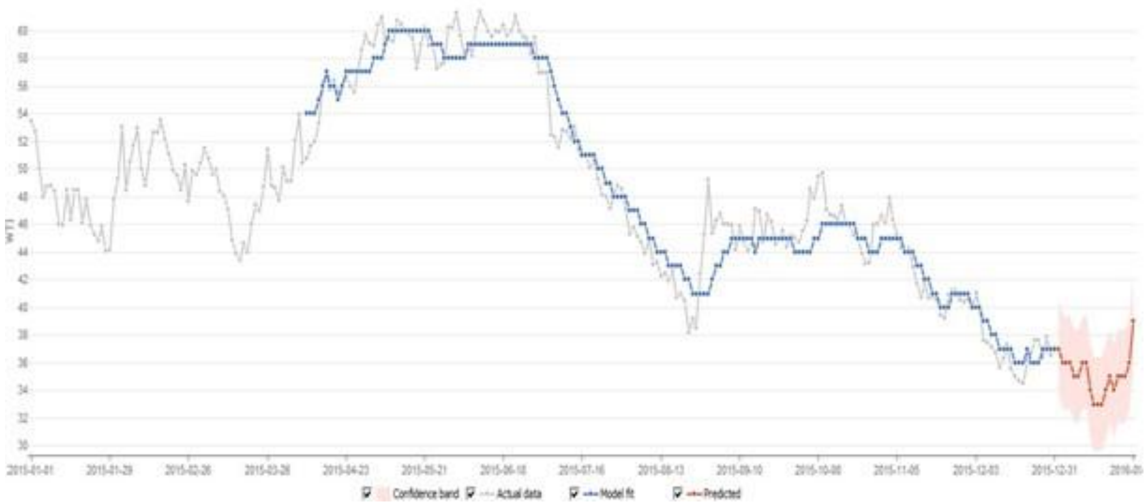



Figure 5: Regression Plots

By experimenting with different numbers of nodes and tapping delay lines, the model specification is trained. Trial and error is used to estimate the number of neurons in the buried layer. The trials initialise with two nodes at error first. Once 15 nodes have been used, the process is repeated. The number of tapped delay lines, on the other hand, was first set at 2 steps and increased to 4 steps. It was done to compare the MSE value across all networks. The ideal network will be the one with the lowest MSE value. Using the training procedure, 12 nodes in hidden layers and 2 tapped delay lines yield the lowest MSE value. A high R value (0.99855) at 12 further supports this finding.

**Prediction Model**




According to our findings, neural networks can accurately anticipate the direction of the price of crude oil (red curve). We can determine the model fit (blue curve), which matches to the observed trend, using the training regression plot shown above (Figure 4). In fact, we find a strong association and a small mean squared error term. By providing insight into the market's future trajectory for oil prices, dynamic neural networks can be useful to investors and decision-makers.

## V. Conclusion

Following a quick review of the literature on forecasting crude oil prices, we presented a NARX model for predicting short-term crude oil prices in this study. Traditional and statistical econometric models for predicting crude oil prices are in fact inadequate when taking into consideration the volatility of crude oil price and nonlinearity of its time series. Following a discussion of this methodology, we decided to use a dynamic ANN as a nonlinear artificial model to predict the short-term price of crude oil. In this experiment, we evaluate the NARX method's capacity for precise prediction. We come to the conclusion that artificial neural networks are more predictive in predicting the price of crude oil. Our ongoing investigation into other methods might result in an improvement.

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