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Prince Sultan University

International finance group of Tunisia



forecasting

provides a literature review on the various techniques that have been used

to forecast crude oil price. We mainly focused on the researches that have

utilized

artificial

neural

network

models

in

their

The literature on forecasting the ‘‘black gold’’ price is vast. This paper

study.

Therefore, a detail description of this model is presented in this paper.

**Submitted:** September 27, 2014.

Manel Hamdi

Submission Number: EB-14-00800

Forecasting Crude Oil Price Using Artificial Neural Networks: A

Literature Survey



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*Saud University, Riyadh, Saudi Arabia*

*Abstract*

Among many and different forecasting models that have been developed to predict the "black

technique to forecast oil price. Based on the GARCH properties of the oil price volatility,

(1998) suggested a semi-parametric approach based on the filtered historical simulation

(1998) applied cointegration analysis to predict the WTI crude oil price. Barone-adesi et al.

sophisticated econometric model for predicting oil price in the 1980s. In another work, Gulen

a small-scale econometric model for oil market prediction. Huntington (1994) utilized a

The first research about forecasting oil market is proposed by Amano (1987). The author used

by academic researchers.

gold" price, the traditional statistical and econometric methods are the first ones to be applied

Morana (2001) employed a semi-parametric approach investigated by Barone-adesi et al.

**Application of Traditional and Statistical Econometric Models**

**2.1**

**Crude Oil Price Prediction: A Literature Review**

**2.**

regression model for short-term monthly prediction of WTI crude oil spot price. In a related

methodology

to short term quarterly WTI crude oil spot

applied an econometrics forecasting

crude oil prices. Using OECD stocks, non-OECD demand and OPEC supply, Zamani (2004)

to the linear forecasting model suggested by Ye et al. (2002, 2005) to predict short-run WTI

study, Ye et al. (2006) included nonlinear variables such as low- and high- inventory variables

inventory levels and relative stock inventories, Ye et al. (2002, 2005) adopted a simple linear

(2002) utilized a nonlinear regression to predict OPEC basket price. Using OECD petroleum

Tang and Hammoudeh

In another work,

(1998) to short-term forecast of Brent crude oil price.

1995), it is also strongly related to irregular and unforeseen events caused by weather, wars,

expectations can significantly affect the price of oil (Bernabe et al., 2004;

and

investors‟

growth, stock levels inventories, foreign exchange rates, world population, political aspects

Beidas-Strom and Pescatori, 2014). Many other factors like Gross Domestic Production

such a strongly debated issue (Kilian and Murphy, 2011; Fattouh, 2012 ; Kilian et al., 2013 ;

activity, and especially that of the speculation, in oil price formation has recently become

embargoes and revolutions (Aloui et al. 2012). Moreover, the important role of financial

Ghouri, 2006; Nelson et al., 1994; Yousefi and Wirjanto, 2004). Furthermore, the time to ship

The price of oil is essentially determined by its supply and demand (Hagen, 1994; Stevens,

a very challenging task which drew the interest of researchers, practitioners and institutions.

for the world‟s economy. Therefore, forecasting crude oil price has always been considered as

As the most important strategic resource

around the globe, crude oil is the “key” commodity

**Introduction**

**1.**

crude oil from one country to another can affect directly their price because oil prices vary in

different regions of the worldwide (Wang et al., 2005a). All these factors can explain the

nonlinear evolution and chaotic behavior of crude oil prices and therefore the high volatility

of crude oil market (Plourde and Watkins, 1994; Yang et al., 2002). The oil price fluctuations

‟s

have a direct effect on the nation

economy (Hamilton, 1996, 2010; Blanchard and Gali,

2007; Kilian, 2008); therefore, it is of vital importance to predict oil price.

The present paper is organized as follows. Section 2 outlines the numerous studies which used

traditional and statistical econometric models to forecast crude oil price. Then, a detailed

description of artificial neural network model was introduced. In addition, we present the

existing literature on crude oil price forecasting using this model. Finally, we conclude in

section 3.

**2.2.1.1 Definition**

inventory adjustment can be slow to happen which explains the major part of the difference

between real and forecasted prices, especially for the short run (Hamilton, 2008). On the other

hand, traditional statistical and econometric techniques are usually able to capture only linear

process in data time series (Weigend and Gershenfeld, 1994). However, the oil prices

behavior is characterized by a high nonlinearity and irregularity. Therefore, the mentioned

models are not the appropriate choice to forecast the oil price.

**2.2 Artificial Neural Network (ANN): Model Description**

**2.2.1 Definition and Neuron Model Evolution**

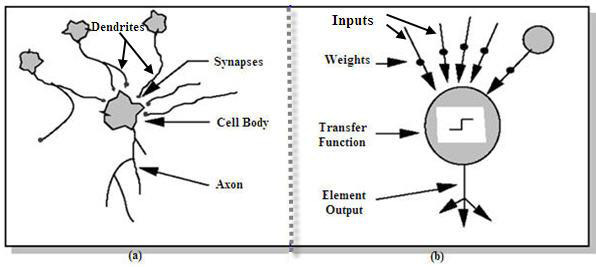
used factors. Supply and demand are relatively inelastic to price changes, subsequently, an

ANN is an input-output mathematical model inspired from human brain functioning by

adopting the same mode of acquiring knowledge through learning process. Fig. 1 summarizes

an analogy between biological and artificial neuron.

**Figure 1.** Analogy between biological neuron (a) and artificial neuron (b)



Narayan (2007) and Agnolucci (2009) used GARCH model to forecast spot and futures crude

correction models. Sadorsky (2006) applied multiple univariate and multivariate statistical

models such as GARCH, TGARCH, AR, and BIGARCH to daily forecast of volatility in

petroleum futures price returns. Slightly more recent, Dees et al. (2007) developed a linear

model of the world oil market to predict oil demand, supply, and prices focusing mainly on

OPEC behavior. Murat and Tokat (2009) investigated the relationship between futures and

spot crude oil prices and therefore tested the ability of futures prices to forecast spot price

movements using random walk model. Cheong (2009) adopted ARCH models to forecast

crude oil markets. On the other hand, more recent studies have applied GARCH as well as

different models of the GARCH family to predict oil price. For example, Narayan and

price. Lanza et al. (2005) investigated crude oil and product prices by utilizing the error

oil prices. In a related research, Mohammadi and Su (2010) compared the forecasting results

of various GARCH-types models in order to predict the crude oil price. Kang et al. (2009)

proposed CGARCH, FIGARCH and IGARCH models to forecast volatility of crude oil

markets. For the same pupose, Wei et al. (2010) extended the study of Kang et al. (2009) by

applying linear and nonlinear GARCH-class models.

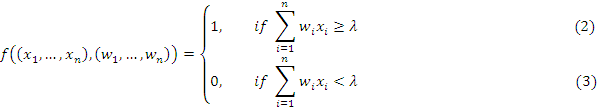
As results of the application of linear techniques, a significant error has been demonstrated

between actual and predicted oil prices. With these models, several exogenous variables have

been employed to predict oil price, however; inventory, supply and demand are the mostly

*y*

**Figure 2.** Illustration ofMcCulloch & Pitts (1943) neuron



neuron defined as:

*f*

is the output of McCulloch-Pitts

is the threshold and

is the sign function,

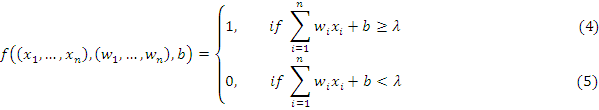
neuron.



*n*

2

1



separator. Thus, the following equation describes the perceptron output :

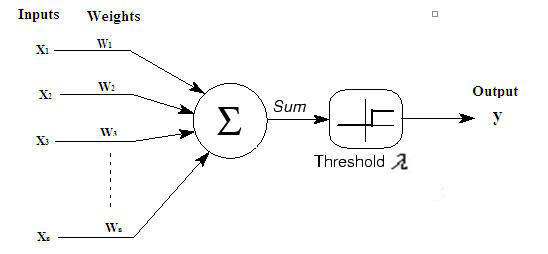
space of input variables into two regions according to a linear decision boundary called linear

perceptron, as the first artificial neuron introducing the learning rule. The perceptron splits the

Rosenblatt (1958) introduced an improved version of McCulloch-Pitts neuron model, a

**b) Perceptron model (Rosenblatt 1958)**

binary values (zeros or ones),



*y*





*i*

*i*





(1)

*w x*

*f*

=

=1











*n*

Mathematically, the McCulloch-Pitts neuron model can be written as follows:

McCulloch and Pitts (1943) proposed the first artificial neuron also called formal neuron.

**a) McCulloch & Pitts (1943) neuron model**

1

weights received by the

are the connections

*w*

,...,

,

*w w*

‟

*n*

2

**2.2.1.2 Neuron Model Evolution**

*x*

...,

,

represent the McCulloch-Pitts neuron inputs that are exclusively

Where

, *x*

*x*

*i*









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

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







*y*

*h*

*w*

*j*

*k*

(for example, with one hidden layer) is :

a single direction„„forward‟‟

In this network system, the information propagates in

: the input

units pass the information to the neurons in the first hidden layer, the outputs from the first

hidden layer are subsequently passed to the next layer, and so forth. Thus, the network output

*g*





*J*

*I*

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2

1

1

2

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*i*



*j*

*i*

1

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,

*w i*

*j*

*x*

*b*

*j*

*b*

*k*

,

(6)

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

*k*

is the threshold and

2

*n*

*n*



weights received by the neuron.

is the sign function,

1

represents

*b*

*f*

the bias measure.

‟s

**Figure 3.** Illustration ofRosenblatt

(1958) neuron

Where

*w w*

,

,...,

*w*

*x*

, *x*

represent the Rosenblatt

neuron inputs,

,

are the synaptic

...,

*x*

1

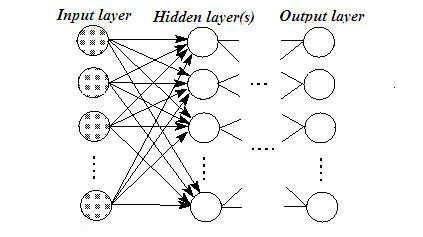
2

The multilayer perceptron is composed of a layer of input units, one or more hidden layers

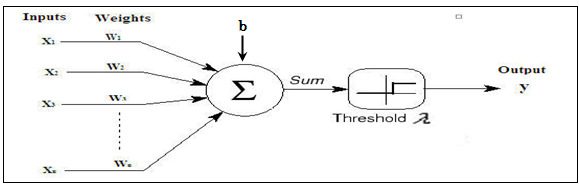
and an output layer (see Fig .4).

**Figure 4.** Illustration ofmultilayer perceptron net

Rumelhart et al. (1986).



consisting in modifying the connections



**c)** **Multilayer perceptron model**

Perceptron neural nets without hidden layers suppose only binary values of input-output as

well as only two layers which explains the capability of the model to treat only the linearly

separable functions. Windrow and Hoff (1960) introduce a learning rule called the delta rule

‟

‟s

weights in order to reduce the difference between

desired and actual output value. Therefore, the output value can take any value instead of 0

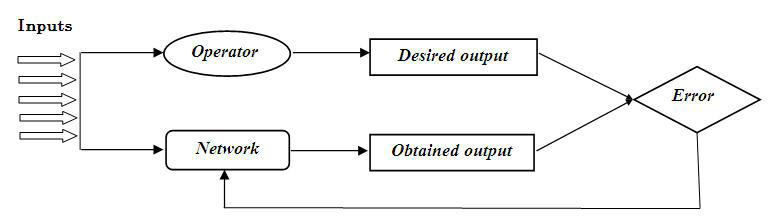
and 1. Minsky and Papert (1969) highlighted, in their book, the utility of adding one or more

hidden layers to detect the complex features present in the inputs. The multilayer perceptron

net was trained, traditionally, based on the backpropagation learning algorithm (detailed in the

next section) developed by

this category of learning.



**Figure 5.** Supervised learning

networks trained with backpropagation learning algorithm (defined later). Fig. 5 schematizes

value and the calculated response by the net). This type of learning is mostly used by neural

the rule of error correction (the error is the difference between the desired

adjust weights is

synaptic weights. Weights are usually initiated randomly and the learning rule adopted to

network is forced to converge to a specific final state (target output) by modifying the

the operator is to provide to network both the inputs and the desired responses. Then the

inputs. The most famous ANN based on unsupervised learning is the self-organizing map

competitive learning rule and the outcomes of the network will have the same trend as similar

learning, only inputs were provided to the network. Weights will be adjusted on the basis of a

In the unsupervised learning, there is no external operator that supervises the process of

**Unsupervised learning**

**b)**

In the supervised learning, the presence of an external operator is indispensable. The role of

*w*

2

*w*

*b*

and

is the weights matrix of the output layer;

the weights matrix of the hidden layer;

1

1

is

and *h* are, respectively, the transfer/activation function of the first and the second layer;

total number of nodes in the hidden layer; K is the number of neurons in the output layer; *g*

*i*

*x*

are the input variables of the network; *I* is the number of input variables; *J* is the

**2.2.2.1 Learning Mode**

**Supervised learning**

**a)**

learning :

between neurons until achieving better network response. In fact, there are three modes of

weights

The learning process of the neural net consists in the adjustment of connection

s‟

Where:

**2.2.2 Operating Keys**

.

the hidden layer must be nonlinear (Hornik et al., 1989).

least one transfer function (see the next section for more description of transfer function) of

2

*b*

are the bias vectors of the hidden layer and of the output layer, respectively. To note, at

*W*

are the random

and

are firstly initialized randomly, where

The weights **W**





.

*W*

*network responses*

*Where K is the number of*

*k*

1



*K*

*k*

*k*

connections weights

For more details see the seminal work of Kohonen (1982).

1

*i*

*i*

*W X*

*W*

) of its

each hidden nodes performs a weighted sum (

*d*



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





vector of weights generated, respectively, by the input layer and hidden layer. Using these

*h*

*i*

*h*

*i*

,

*W W*

*‘‘Reinforcement learning is learning what to do*

the most used algorithm is the backpropagation algorithm. This rule consists in adjusting the

choice of the learning rule is needed to deduce a good quality of estimation. In this context,

The learning algorithm is designed to estimate the optimum weights. Therefore the good

**2.2.2.2 Learning Algorithm: The Backpropagation Rule**

Cambridge, MA, A Bradford Book, p. 4).

(Sutton and Barto, 1998. Reinforcement Learning: An Introduction. MIT Press,

*trying them’’*

*forms of machine learning, but instead must discover which actions yield the most reward by*

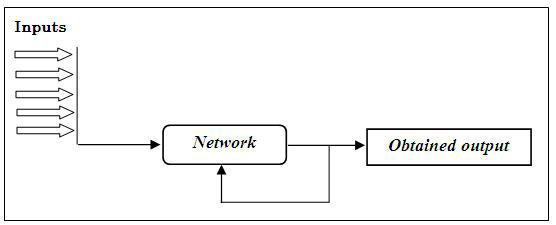
*maximize a numerical reward signal. The learner is not told which actions to take, as in most*

*-how to map situations to actions-so as to*

synaptic connections in order to minimize the error between the calculated or estimated

**Reinforcement learning**

**c)**



**Figure 6.** Unsupervised learning

this class of learning.

classification, pattern recognition, clustering, etc. Fig .6 depicts an explanatory diagram of

. The Kohonen's SOMs are widely applied in several fields such as text

(SOM) of Kohonen

the root mean square error defined as follows:

*E*

(7)

0

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





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1

*K*

2

1

necessary to define an error function to be minimized. This function could be for example ;

The backpropagation algorithm can be applied to any type of error function. Thus, it is

*k*

*k*

0

*d*

response (

of the network.

and the desired response (

)

)

is a mathematical function applied to the weighted

.

The process will be repeated many times until obtaining a negligible output error

*E*

0

**2.2.2.3 Activation/Transfer Functions**

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An activation or transfer function

*f*

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sum

(

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to

determine

,

*with*

*is the learning rate and E is the output error*

the

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

*W*

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however,

ANN model (Gomes et al., 2011).

As

known,

there

are

several

types

of

activation

functions,

algorithms. Therefore, a pertinent choice of this element is required in the specification of an

the

sigmoid

and

hyperbolic tangent functions are the most widely used (Haykin, 1999). Table 1 presents

mathematical definitions as well as graphical representations of some activation functions.

*WX*

activation

or

the

state

of

each

neuron

of

the

net :

*W t*











*f*

*WX*

.

The activation function plays a crucial role in the convergence of the learning

*i*



*O*

*g W f*

(

*W X*

)

(8)

*k*

*h*



*where f*

*and g is the transfer function in the hidden and output layer*

*W X*





*f*

(.)

inputs **X** and then applies the activation function

. Thus,

represents the

*f*

(

*i*

inputs of the output layer (supposing that the network presents only one hidden layer),

thereafter the

output neurons are calculated as follows :

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

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 

*W t*

1

*W t*

*W t*

(9)

 

*E*

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



 





*Where*

activation/transfer function is the most frequently utilized (Van der Baan and Jutten, 2000).

,

*respectively*

.

By using the backpropagation rule as a learning algorithm of ANN model, the sigmoid



After computing the output of the network, the next step consists in comparing the obtained

response to the desired response of the network, therefore takes the error that must be

reduced.

To update the weights of neurons, the error signal is back propagated to the inputs by

modifying synaptic weights such that the error between the calculated and desired output will

be minimized in the next iteration (t+1).

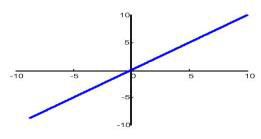


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 

Identity

*WX*



0 si

< 0

*WX*

*WX*

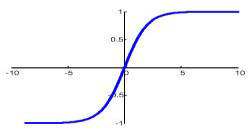






exp

exp





**2.2.3 Performance Criteria**

**2.2.2.4 Stopping Criteria**

The goal of using stopping criterion is to decide when to finish learning process of an ANN to

avoid overfitting problem. According to Shao et al. (2011), the most applied stopping

parameters are, a predefined error output value (the difference between the target output and

the ANN computed output) for training phase, a predetermined number of learning iterations

to reduce this error and finally, a threshold value of learning rate defined as a stop index of

training process.

The use of forecasting evaluation measures is a necessary step to gauge the predictive

capability of the ANN model. To verify the predictive ability, several performance criteria can

be used as good indicators of forecasting performance. Table 2 presents the most frequently

utilized performance criteria to judge the quality of prediction of the employed model (Zhang

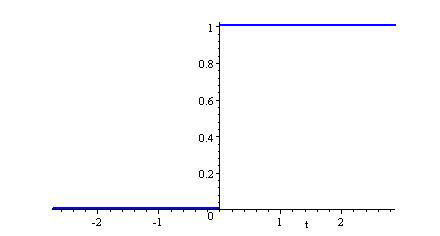
et al., 1998).

Heaviside

1 si

*WX*

0



\_

Sigmoid

1



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



*WX*

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1

***Function***

***Definition***

***Graphic illustration***



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*WX*

*WX*

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exp

exp



tangent







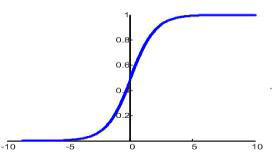


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

*WX*

exp



**Table I.** Activation/Transfer functions

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Hyperbolic

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**E**rror (**NMSE**)

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*i*

**N**ormalized **M**ean **S**quared

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*NMSE*

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*i*

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*MSE*

*SSE*

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1

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*d*

*n*



**M**ean **A**bsolute **P**ercentage **E**rror

*i*

*i*

1

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*d*

*N*

*n*

(**MAPE**)

*MAPE*

\*100

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*i*

This section presents a large search of literature survey on forecasting crude oil price based on

**2.3 Application of ANN Models**

\*N is the size sample

ANN model. Kaboudan (2001) and Rast (2001) are the first to introduce the ANN technique

1

1

1

*i*

*i*

*i*



(MSE=3.54). In the same year, Rast (2001) employed fuzzy neural networks methodology

the feedforward neural network (-22.34%) for the out of sample set.

proposed model improve the prediction accuracy (6.95%) more than the classical technique as

futures contracts will cost less). Based on the performance forecast results, he showed that the

purchasing it by utilizing the future contract; while in the backwardation state, the use of

different oil market states (contango, i.e. purchasing the oil today is less expensive than

for forecasting the future crude oil price. He used oil futures prices time series into two



model (MSE=1.85) outperformed the RW (MSE=2.29) and also the neural network technique

of US imports. Based on MSE measure, he concluded that genetic algorithm forecasting

OECD consumption, world crude stocks, change in US stocks and lagged FOB crude oil price

over the period from 1993 to 1999, namely crude oil spot prices, world crude production,

the monthly crude oil prices. For this purpose, the author used several monthly time series

techniques as genetic programming (GP) and ANN to random walk (RW) model to forecast

in order to predict the price of crude oil. Kaboudan (2001) compared two compumetric

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*i*

*i*

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*i*

*i*

*d*

*d*

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*d*

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1

*SSE*

*n*

**M**ean **S**quared **E**rror (**MSE**)

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1

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*N*

*N*

*i*

*i*



0

*d*

*MSE*

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***formulas***

***Definition***



*i*

*i*

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*d*

*SSE*

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*n*

**S**um **S**quared **E**rror (**SSE**)

2

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1

*n*

**M**ean **A**bsolute **E**rror (**MAE**) index

*i*

1



or Mean Absolute Deviation

(**MAD**)

1

*i*



*N*

*i*

*i*

0

*d*

*MAE*

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

**R**oot **M**ean **S**quared **E**rror (**RMSE**)





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*n*

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

*N*

*i*

*i*

**Table II.** Performance measures

0

*MSE*

*d*

*RMSE*

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

, 2003. Three performance

better

significantly

performs

RMSE=2.85)

and

MSE=8.14

(MAE=2.04,

proposed models. On the basis of these computed measures, they concluded that ANN

metrics (MAE, MSE and RMSE) were utilized to evaluate the forecasting results of the

than

, 1983 and January 13

prices covering the period between April 4

th

th

crude oil futures prices. The data used in this forecasting study are the daily crude oil futures

autoregressive conditional heteroskedasticity (GARCH) models for the daily prediction of

feedforward neural network (FNN), ARMA (autoregressive moving average) and generalized

In the study of Moshiri and Foroutan (2006), three competing tools are proposed such as a

forecaster performs better than the two other models. However, the BPNN surpass SVM and

, 1991 to

daily nearby crude oil futures contract prices over the period from April 16

th

oil futures prices by utilizing technical analysis crossover rules as inputs. To train the model,

Slightly more recent, Shambora and Rossiter (2007) used an ANN model to predict the crude

ARIMA for two sub-periods among four tested sub-periods.

stat

focusing on two forecasting performance criteria (RMSE and Dstat), they found SVM

December 2003. The proposed method was compared to ARIMA and BPNN. As results and

January 1970 to

crude oil price using monthly WTI spot prices over the period from

In next work, Xie et al. (2006) applied a support vector machine (SVM) model to predict

MSE=15.25 and RMSE=3.90).

(MAE=4.81, MSE=29.27 and RMSE=5.41) and also than GARCH model (MAE=2.90,

ARMA

results of these metrics, ANNs with GA model (RMSE=1.2354, MAE=0.8629) offers much

information and the monthly WTI crude oil spot prices ranging from January 1970 to

series, while the BPNN was used to handle the nonlinear part. By utilizing the online retrieved

RES. The ARIMA model is employed for modeling the linear part of crude oil price time

of crude oil price. The impact of the retrieved information was therefore measured by using

WTM was utilized to extract the irregular events, from internet, that can affect the variability

(RES), autoregressive integrated moving average (ARIMA) model and ANN technique.

price forecasting by combining web-based text mining (WTM), rule-based expert systems

In another work, Wang et al. (2005b) applied a TEI@I methodology to monthly crude oil

better performance than VAR technique (RMSE=4.69861, MAE=4.18883).

December 2003, the proposed model was compared to single ARIMA, single ANN and to the

November 2002 using two performance criteria: (RMSE) and (MAE). By comparing the

accuracy was evaluated based on monthly data over the period between January 1986 and

(BPNN) with genetic algorithm (GA)

”. The forecasting

“the backpropagation neural network

money supply, oil supply and petroleum consumptions are used as inputs of the second tool

based on three explanatory variables: oil prices, petroleum consumption and oil supply. While

evolution of U.S. oil price. A vector autoregression (VAR) is the first technique, modeled

integration whereas 2.0350, 2.3336 and 2.3392 for the simple integration, ANN and ARIMA,

was found with ARIMA model (54.17%).

D

forecasting approach, 85.42% for the simple integration, 70.83% for ANN tool and the lowest

stat

≈≈

100%) was achieved with the nonlinear integrated

(

respectively. Also, the higher D

In another research, Mirmirani and Li (2004) applied two different techniques to forecast the

simple integration and for the same period the RMSE was equal to 1.0549 for the nonlinear

entire period of evaluation (2000-2003) was equal to 85.42% whereas only 70.83% for the

in terms of all evaluation statistics used (e.g. the hit rate for the nonlinear integration over the

used. The empirical results show that the TEI@I methodology significantly performs the best

stat

) and the hit ratio are

approach, three performance criteria, RMSE, direction statistics (D

simple integration of ARIMA- ANN. To verify the effectiveness of the nonlinear integration

th

comparison

, the

. According to NMSE and R

paradigm for two different neural network architectures

2

3

evaluate this task, the proposed model was compared to single- scale neural network learning

components are retained among nine as inputs of neural network model for prediction task. To

inputs of neural network. After training process and based on input strength indicator, only six

/10/2006, into different intrinsic mode components that can be used as

/01/1998 to 30

01

results

st

method consists on decomposing the original daily crude oil price time series, running from

empirical mode decomposition method to predict the WTI crude oil price. The decomposition

Also, Yu et al. (2007) proposed a multiscale neural network learning paradigm based on

tool; markov chain based semiparametric model, RBF neural network and wavelet analysis).

single models (1.02980, 2.70602, 2.81591 and 4.52168 respectively for combined forecasting

criterion, the authors showed that the proposed forecasting method outperforms the others

evaluation metric. Based on this

results, MSE was used as a performance

forecasting

, 2006. To assess the simulation

, 1987 to August 30

paradigm performs better than the single-scale learning paradigm and especially with (6:15:1)

as inputs, 15 hidden nodes and one output and the second neural network design adopted is (6:15:1) .

The first neural network configuration used is (9:15:1) that represents 9 intrinsic mode components utilized

3

See the research paper of Wang et al. (2004) for more explanation of this approach.

2

(0.9876).

architecture which represents the lowest error (0.0084) and the highest R

2

crude oil price ranging from May 20

architectures. For the same neural network design, the multiscale neural network learning

both

for

paradigm

learning

multiscale

the

of

superiority

a

showed

such as the FNN, GA and the K-means

the

compared

authors

the

model,

proposed

the

of

effectiveness

assess

To

clustering.

prediction results of the hybrid model with the forecasts of four single models namely Short

popular artificial intelligence (AI) techniques

tool to forecast the monthly WTI crude oil price. The hybrid model is composed of three

In another study, Amin-naseri and Gharacheh (2007) proposed a hybrid artificial intelligence

benchmark models indicating inefficiency of the crude oil futures market.

As results of this empirical study, the profitability of ANN performs better than the other

such as buy-and-hold strategy, traditional technical trading strategy and a naïve RW strategy.

Besides, the authors compared the neural network model to three benchmark trading strategies

profitability has been conducted using several means and statistical measures and factors.

prices which are considered as trading signals. Therefore, an empirical investigation of

, 1997 are employed. The outputs of the neural network represent the predicted

December 1

stat

th

th

method and wavelet decomposition analysis. For the simulation task, the authors used Brent

work as the radial basis function (RBF) neural network, markov chain based semiparametric

network approach. More precisely, a combined three forecasting tools were applied in this

For the same purpose of predicting crude oil price, Liu et al. (2007) employed a fuzzy neural

empirical comparison study.

significantly others techniques in terms of the majority of performance measures used for

)), hybrid model results outperform

(R

process) and the squared correlation coefficient

2

st

, U2-Theil (RMSE of the model/ RMSE of RW

MAPE, Max AE, SSE, MSE, RMSE, D

period from January 1974 to December 2001. Based on nine performance criteria (MAE,

price data of the fourth and last experiment (comparison with ANN) was selected over the

December 2002 for the third experiment (comparison with the third model). Finally, the oil

December 1999 for the second (comparison with GP) and running from January 1983 to

2006 for the first experiment (comparison with the first model) while from January 1974 to

price time series used in their empirical study were selected from January 1983 to December

, and ANN technique. The WTI Crude oil

term energy outlook, GP, AI framework system

2

=0.225 and D

decrease‟, „decrease‟, „constant price‟, „increase‟, „strong increase‟)

they employed five neurons in the output layer that represent five trend classes („strong

at forecasting the trend of WTI price development and not the exact WTI price value. Hence,

perceptron was shown as the optimal design. More precisely, Lakes and his colleagues aimed

oil market from 1999 to 2006. Several network architectures were built and the three layer

economic and political influencing features) which have a meaningful influence on the crude

quarter ahead). They used a lot of available relevant factors (supply and demand as well as

development in short-term (one week ahead), mid-term (one month ahead) and long-term (one

Recently, Lackes et al. (2009) proposed the backpropagation FNN to forecast crude oil price

stat(BRENT)

(BRENT)

=87.81%).

, they also tried with two

RMSE

stat(WTI)

(WTI)

=86.99%;

D

=0.273 and

(RMSE

the best for the two time series under study

stat

, the empirical results have shown that the EMD-FNN-ALNN significantly perform

and D

(2009)

and RMSE as performance criteria, they concluded that the futures prices especially futures

time series for the period ranging from September 1996 to August 2007 and based on hit rate

prices. Using WTI crude oil spot prices and futures prices (1, 2, 3 and 4 months to maturity)

ahead). Moreover, these authors tested the relationship between futures and spot crude oil

backpropagation algorithm to predict the crude oil spot prices on the short term (three days

with

model

ANN

an

presented

Averaging, standard FNN and the single ARIMA. Based on two main indicators as the RMSE

Haidar

and

Kulkarni

study,

recent

another

In

especially in the mid and long term which reach more than 90% whereas 69% in short-term.

prediction with two classes was explicitly superior than trend forecasting with five classes,

measure of the hit rate as the forecasting performance criterion, they concluded that the trend

output neurons corresponding an „increase‟ and a „decrease‟ trend prediction. Based on the

purpose.

MSE, MAE and SSE, Haidar and his colleagues concluded that futures contracts mainly 1 and

,

several performance criteria such as the hit rate, information coefficient (IC), RMSE, R

2

price. These features were selected over the period from 1996 to August 2007. Based on

the second is composed of S&P 500, gold spot price, dollar index and the heating oil spot

as inputs of the forecasting model. The first represents the WTI crude oil futures prices while

predict the short-term of crude oil spot price. Two groups of daily variables were considered

In their research study, Haidar et al. (2008) developed a three layer backpropagation FNN to

concluded that ANFIS methodology can provide a good forecasting ability.

authors

The

2 months to maturity improve the prediction results, and also outperform all other inputs for

verification

and

checking

for

2003

December

to

1999

February

been trained focused on price data ranging from July 1973 to January 1999, and from

oil prices. The future oil price depends only on its past price history. The proposed model has

th

EMD-ARIMA-

EMD-ARIMA-ALNN,

EMD-FNN-Averaging,

the

as

such

techniques

testing and verification, the authors have compared the proposed model with five others

/09/2006 for WTI and BRENT, respectively. For the purpose of

/05/1987 to 30

and from 20

th

Gori et al. (2007) utilized adaptive neuro-fuzzy inference system (ANFIS) to predict monthly

/09/2006

/01/1986 to 30

utilized a daily data of crude oil price over the period between 01

th

st

linear neural network (ALNN) in the price forecasting task. In this research, they have

learning paradigm applies the decomposition technique with three-layer FNN and an adaptive

network learning approach to forecast both WTI and BRENT crude oil prices. The proposed

Moreover, Yu et al. (2008) used an empirical mode decomposition (EMD) based neural

ability of the employed model for multiple steps prediction.

one step forecast. Moreover, they found that heating oil spot price improves the forecasting

conditions,

important prediction results were demonstrated. In March 2008, the error simulation value

more

significantly

therefore

inputs

to

index

crisis

the

included

authors

the

was equal to 2.58 and 41.31 for the model included crisis index and without crisis index

critical

in

While

prediction.

good

a

showed

simulations

error

the

case,

this

Integration

metrics.

Dstat

and

RMSE

on

based

model

EMD-FNN-ALNN

and

model

In

finding, the authors compared this approach to two other hybrid models as TEI@INonlinear

Dstat (93.33%); the authors showed the reliability of this prediction tool. To validate this

on the results of three performance measures such as NMSE (0.00896), RMSE (2.2690) and

total of 22 sub-indicators of population, economy, inventory, supply and demand. By focusing

qualitative data was derived from online news, whereas the quantitative variables represent a

varying from January 1984 to February 2009, was used as inputs of the proposed model. The

forecast the monthly WTI crude oil price. A combination of qualitative and quantitative data,

Abdullah and Zeng (2010) applied the machine learning and ANNs-quantitative approach to

crude oil price.

critical situation periods presents a great importance to improve the forecasting accuracy of

respectively. Based on these results, the authors concluded that introducing crisis index in

improve

st

surpasses the PCP of model (2) for several arbitrary selected periods. For example, for the

percentage of the correct prediction (PCP) and found therefore that PCP of model (1)

the

determined

authors

The

predictions.

model

the

of

accuracy

st

to

algorithm

procedure (model 2), the empirical findings showed a great advantage of the smoothing

By comparing the smoothing procedure model (model 1) to the model without smoothing

, 2007.

, 2004 to April 30

algorithm to the daily crude oil spot prices running from January 5

th

th

predict the daily variation of the WTI crude oil price. Furthermore, they applied a smoothing

Furthermore, Ghaffari and Zare (2009) combined the ANNs and the fuzzy logic approaches to

prediction accuracy of the crude oil price direction for the short term.

crude oil price used in this research was the Europe (UK) Brent Blend spot price covering the

crisis.

normal conditions, they only utilized six main factors as inputs due to absence of important

general regression neural network model in two different conditions (normal and critical). In

behavior. In this research, Alizadeh and his colleague investigated the forecasting ability of

crisis index was also used to overcome unforeseen world events that can affect oil price

capacity, OPEC crude oil production ceiling allocation and US gasoline ending stocks. A

gross domestic product growth, US dollar nominal effective exchange rate, OPEC total liquid

the proposed network, the authors employed six factors, namely, US refinery capacity, US

as the general regression neural network to forecast monthly Brent crude oil price. As input of

In another research, Alizadeh and Mafinezhad (2010) proposed an intelligent forecasting tool

authors showed that the wavelet decomposition method improves the forecasting accuracy.

period running from January 1997 to October 2008. Focusing on the simulation results, the

contracts 1 and 2 add newer information to the spot price and therefore, improve the

for hidden nodes and one output neuron that represent the future crude oil price. The world

input layer of the network. Hence, the proposed network was composed on four input nodes,

decomposed the original crude oil price into three decomposed levels which are used as the

neural network for crude oil price forecasting. The wavelet transform of Mallat algorithm

In the same year, Qunli et al. (2009) simultaneously applied a wavelet transform and RBF

disturbances while maintaining the dynamic crude oil process.

especially the capability of the smoothing procedure to reduce the unforeseen short term

respectively. These findings highlighted the reliability of the proposed model (model 1) and

/5/2007), the PCP equals to 45.45% and 68.18% for model (1) and (2),

/5/2007-31

period (1

01/1986 - 11/2002

Mirmirani and Li (2004)

BPNN with GA and VAR

Kaboudan (2001)

GP, ANN, RW

1993 - 1999

Rast (2001)

Fuzzy neural networks

NA

Moshiri and Foroutan (2006)

ANN, ARMA, GARCH

04/04/1983 - 13/01/2003

4

The prediction accuracy has mainly been evaluated based on symmetric MAPE (SMAPE) and mean absolute

scaled error (MASE) performance criteria.

(ARIMA+ANN)

–

Wang et al. (2005)

TEI@I methodology

01/1970

12/2003

(nonlinear integration)

ARIMA

ANN

Simple integration

and

tangent transfer function (MSE=3.59066, MAE=1.10108, hit rate=80% and R

=0.9988),

outperforms

the

multilayer

BPNN

(MSE=4.48590,

MAE=1.40342,

hit

rate=76%

2

2

R

=0.9892).

In a more recent research, Xiong et al. (2013) proposed an EMD analysis based on the FNN

modeling incorporating the slope-based technique (SBM) to forecast the crude oil price for

multi-step-ahead. To investigate the forecasting performance of the proposed model, the

authors have examined and compared three multi-step-ahead prediction strategies including

iterated strategy, direct strategy, and MIMO (multiple-input multiple-output) strategy using

th

BPNN and the Haar A Trous wavelet decomposition to forecast the short term crude oil price.

less than TEI@INonlinear Integration model (1.0579) and also less than EMD-FNN-ALNN

model (0.2730). Nevertheless, TEI@INonlinear Integration forecasting model presents the

highest D

(95.83%) and slightly less important D

value (93.33%) with ANN-quantitative,

stat

stat

however, 86.99% with EMD-FNN-ALNN model. Consequently, the high directional accuracy

(93.33%) proved the effectiveness of this predicting tool.

More recently, Jammazi and Aloui (2012) employed a hybrid model combining the multilayer

th

The crude oil data frequency used in this empirical investigation is the monthly spot price of

WTI over the period ranging from January 1988 to March 2010. To provide the best

forecasting simulation results, the authors used different neural network architectures as well

as three kinds of transfer function as the sigmoid, the bipolar sigmoid and the hyperbolic

2

tangent. Four performance metrics (MSE, MAE, hit rate and R

) were chosen by the authors

to testify the forecasting ability of the proposed technique. The comparative empirical

findings show that the hybrid model, which combine 3 input-3 hidden nodes to hyperbolic

**Periods**

**Author(s)**

**Technique(s)**

0.948 and 0.914 respectively for EMD-SBM-FNN strategy, direct EMD-SBM-FNN strategy,

the weekly WTI spot price over the period (07

/01/2000-30

/12/2011). On the basis of

4

prediction accuracy

and computational load, they concluded that the employed EMD-SBM-

FNN model using the MIMO strategy is the best compared to others strategies. To justify this

conclusion, let‟s refer back to

the example of 12-step-ahead where MASE is equal to 0.991,

Corresponding to RMSE comparison results, the ANN-quantitative model (2.2690) performs

and MIMO EMD-SBM-FNN strategy. Table 3 presents a summary of literature on oil price

prediction.

**Table III.** A Survey on world oil price prediction

Alizadeh

neural network

01/1997 -10/2008

Wavelet transform and RBF

Qunli et al. (2009)

Abdullah and Zeng (2010)

network

(2010)

NA

General regression neural

Mafinezhad

and

08/2007

09/1996

ANN

Kulkarni and Haidar (2009)

–

ANFIS

05/01/2004 - 30/04/2007

Machine learning, ANNs-

Ghaffari and Zare (2009)

data.

to forecast crude oil prices. These methods are usually able to handle only linear time series

introducing numerous studies which have used traditional and statistical econometric models

In this paper, we surveyed a literature on forecasting crude oil price. Firstly, we began by

**3. Conclusion**

\*NA: not available

However,

strategy

MIMO EMD-SBM-FNN

market.

a strong predictive ability, in this field of research.

ANNs models. As conclusions drawn from these studies, neural network approach has shown

approach. Finally, we presented the existing literature on forecasting crude oil price using

nonlinear AI model used to predict crude oil price. Therefore, we have well described this

forecasting oil price via nonlinear models is the appropriate choice. ANN is the most popular

Therefore,

strategy,

commodities

volatile

most

the

is

market

oil

crude

03/2010

01/1988

Multilayer BPNN and the

Jammazi and Aloui (2012)

–

Haar A Trous wavelet

quantitative

01/ 1984 - 02/2009

direct EMD-SBM-FNN

EMD-SBM-FNN strategy,

07/01/2000-30/12/2011

EMD-SBM-FNN

Xiong et al. (2013)

decomposition

FNN, GA, K-means

clustering

(2007)

12/2006

01/1983

Amin-naseri and Gharacheh

–

20/05/1987 - 30/08/2006

Fuzzy neural network

Liu et al. (2007)

01/ 1970 - 12/ 2003

SVM , ARIMA, BPNN

Xie et al. (2006)

and

(2007)

16/04/1991 - 01/12/1997

ANN

Rossiter

Shambora

(BRENT: 20/05/1987 -

–

and

EMD-ARIMA-ALNN,

30/09/2006)

EMD-FNN-Averaging,

(WTI: 01/01/1986 -

EMD-FNN-ALNN,

Yu et al. (2008)

EMD-ARIMA

1999 - 2006

Backpropagation FNN

Lackes et al. (2009)

FNN and ARIMA

30/09/2006)

Averaging,

ANFIS model

Gori et al. (2007)

–

07/1973

learning paradigm

01/01/1998 - 30/10/2006

Multiscale neural network

Yu et al. (2007)

FNN

1996 - 08/2007

Three layer backpropagation

Haidar et al. (2008)

12/2003

Beidas-

so different from 1970s?‟‟ NBER working p

Blanchard, O. J. and Gali, J. (2007) „„The macroeconomic effects of oil shocks: Why are the

*Applications* **338**(3), 567-584.

*Physica A: Statistical Mechanics and its*

approach for describing crude oil price dynamics

‟‟

A multi-model

Bernabe, A., Martina, E., Alvarez-Ramirez, J. and Ibarra-Valdez, C. (2004)

„„

IMFworking paper *(WP/14/218)*.

Oil price volatility and the role of s

2000s

peculation‟‟

Strom, S. and Pescatori, A. (2014) „„

100-104.

*Risk* **11**,

Barone-Adesi, G., Bourgoin, F. and Giannopoulos, K. (1998)

„„Don‟t Look Back‟‟

160-167.

*Conference on Engineering Applications of Neural Networks (CEANN’2007),*

*The Proceedings of the 10th International*

monthly forecasting

of crude oil price time series‟‟

*Energy Policy* **35**, 178-191.

*Energy Economics* **31**, 531-536.

based on soft computing

‟‟

A novel algorithm for prediction of crude oil price variation

Ghaffari, A. and Zare, S. (2009)

„„

*and Economics (Re3)*, 1-5.

*Review of Environment, Energy*

Speculation and oil price f

ormation‟‟,

Fattouh, B. (2012) „„

A hybrid artificial intelligence approach to

oil market: assessment of a quarterly economet

ric model‟‟

Modelling the world

Dees, S., Karadeloglou, P., Kaufmann, R. K. and Sanchez, M. (2007)

„„

*Energy Policy* **37**, 2346-2355.

models‟‟

Modelling and forecasting crude oil markets using ARCH-type

Cheong, C.W. (2009)

„„

13368, 1-77.

aper number

(2010)

K

Mafinezhad,

and

A.

Alizadeh,

„„

*Energy Economics* **31**, 316-321.

of GARCH and implied volatility models

‟‟

Volatility in crude oil futures: A comparison of the predictive ability

Agnolucci, P. (2009)

„„

Monthly

1-8.

*International Joint Conference on Neural Networks (IJCNN’2010),*

*Proceedings of the*

prediction with Artificial Neural Networks-Quantitative (ANN-Q) model

‟‟

for crude oil price

Machine learning approach

Zeng, X. (2010)

Abdullah, S. N.and

„„

Aloui, C. Hamdi, M., Mensi, W. and Nguyen, D. Y. (2012)

Amin-Naseri, M. R. and Gharacheh, E. A. (2007)

„„

*Modeling* **9**(4), 615-635.

*Journal of Policy*

A Small Forecastin

Amano A. (1987)

g Model of the World Oil Market‟‟

„„

*Energy Studies Review* **19**(2), 38-51.

varying efficiency of crude oil markets

‟‟

Further evidence on the time-

**References**

„„

, 2, 465-468.

*On Electronics And Information Engineering (ICEIE*

*’2010)*

*Proceedings of the International Conference*

Artificial Neural Networks and A Crisis Index

‟‟

Using

Forecasting

Price

Oil

Brent

rks: A comprehensive foundation‟‟

Huntington, H. G. (1994)

‟‟

„„

*Neural Networks* **2**, 359-366.

universal

approximators‟‟

-layer feedforward networks are

Hornik, K., Stinchcombe, M. and

White, H. (1989) „„Multi

Jersey.

*Prentice Hall,* New

Neural netwo

Haykin, S. (1999)

Oil Price Forecasting in the 1980s: What Went Wrong?

„„

103-108.

*Sensors, Sensor*

*Networks and Information Processing (ISSNIP ‘2008),*

*Intelligent*

*on*

*Conference*

*International*

*the*

*of*

*Proceedings*

networks‟‟

neural

*Congress on*

*Energy Economics* **31**, 119-125.

Markets‟‟

Forecasting Volatility of Crude Oil

Kang, S.H., Kang, S.M. and Yoon, S.M. (2009)

„„

*Evolutionary Computation* **1**, 283-287.

artificial

Compumetric forecasti

Kaboudan, M. A. (2001)

ng of crude oil prices‟‟

„„

*Energy Economics* **34**(3), 828-841.

wavelet decomposition and neural network modeling

‟‟

Crude oil price forecasting: Experimental evidence from

Jammazi, R. and Aloui, C. (2012)

„„

*Energy Journal* **15**(2), 1-22.

*The*

in

1296.

*Energy* **32**, 1291-

short term under three scenarios: Parabolic, linear and chaotic behavior

‟‟

Forecast of oil price and consumption in the

Gori, F., Ludovisi, D. and Cerritelli, P.F. (2007)

„„

*Computing and Applications* **20**(3), 417-439.

*Neural*

fo

for

network

neural

„„

functions

activation

series‟‟

time

financial

recasting

Comparison of new

Gomes, G. S. D. S., Ludermir, T. B. and Lima, L. M. M. R. (2011)

„„

*Energy Policy* **34**, 3327-3333.

Assessment of the relationship between oil prices and US oil stocks

Ghouri, S. S. (2006)

‟‟

„„

rices‟‟

Forecasting model for crude oil prices based on

Haidar, I., Kulkarni, S. and Pan, H. (2008)

„„

16186, 1-22.

working paper number

NBER

Nonlinearities and the macroeconomic effects of oil p

Hamilton, J

rices‟‟

. D. (2010) „„

*Association for Energy Economics* **30**(2), 179-206.

*The Energy Journal, International*

Understanding crude oil p

Hamilton,

J. D. (2008) „„

*Journal of Monetary Economics* **38**(2), 215-220.

-

Hamilton,

Macroeconomy relationship‟‟

J. D. (1996) „„This is what happened to the Oil

*Review* **18**, 145-158.

*OPEC*

Hagen, R. (1994) „„How is the international price of particular crude determined?‟‟

*Finance and Development* **3**, 13-21.

*Journal of Energy*

Efficiency in the Crude Oil Futures

Gulen, S. G. (1998)

Markets‟‟

An

*Advances in Econometrics* **19**, 203-223.

algori

thm in forecasting price of oil‟‟

A comparison of VAR and neural networks with genetic

Mirmirani, S. and Li, H.C. (2004)

„„

*The MIT Press,* Cambridge, MA.

Geometry

‟‟

Computational

to

Introduction

„„

Perceptrons:

(1969)

S.

Papert,

and

M.

Minsky,

„„

*Bulletin of Mathematical Biophysics* **5**, 115-33.

nervous activity‟‟

A logical calculus of the ideas immanent in

McCulloch, W. S. and Pitts, W. A. (1943)

„„

‟‟

*Energy Economics* **31**(1), 85-90.

Futures

‟‟

Forecasting Oil Price Movements with Crack Spread

Murat, A. and Tokat, E. (2009)

„„

*Energy Journal* **27**, 83-97.

*The*

Forecasting Nonlinear Crude Oil Future Prices

Moshiri, S. and Foroutan, F. (2006)

„„

*Economics* **23**, 325-338.

*Energy*

A semiparametric approach to short-term oil price forecasting

Morana, C. (2001)

‟‟

„„

*Energy Economics* **32**, 1001-1008.

Applications of ARIMA

–GARCH Models‟‟

International Evidence on Crude Oil Price Dynamics:

Mohammadi, H. and L. Su. (2010)

*Working paper*. University of Michigan.

*Information Security* **2**(1), 81-88.

*International Journal of Computer Science &*

neural networ

ks and commodity futures prices‟‟

Forecasting model for crude oil price using artificial

Kulkarni, S. and Haidar, I. (2009)

„„

*Biological Cybernetics* **43**, 59-69.

Self-

Kohonen, T. (1982)

Organized Formation of Topologically Correct Feature Maps”

“

global market for crude o

il”

ventories and speculative trading in the

Kilian, L. and Murphy, D. P. (2011)

“The role of in

*The Energy Journal* **34**(3), 7-33.

have we learned so f

ar?”

arkets: What

Kilian, L., Fattouh, B. and Mahadeva, L. (2013)

“The role of speculation in oil m

*Literature* **46**(4), 871-909.

*Journal of Economic*

Kilian, L. (2008)

*Lecture Notes in Computer*

*Knowledge Discovery (FSKD '2007),* 273-277.

*Proceedings of the Fourth International Conference on Fuzzy Systems and*

neural network‟‟

A new approach to forecast crude oil price based on fuzzy

Liu, J., Bai, Y. and Li, B. (2007)

„„

*Energy Economics* **27**, 831-848.

relationships among heavy oil and product prices

‟‟

Modeling and forecasting cointegrated

Lanza, A., Manera, M. and Giovannini, M. (2005)

„„

*Science* **5518**, 248-255.

“The Economic effects of energy price shocks”

Development of Crude Oil with Artificial Neural Networks

‟‟

Price

the

Forecasting

(2009)

M.

Dirkmorfeld,

and

C.

R., Börgermann,

Lackes,

„„

*Economics* **28**, 467-488.

Neural-Network-Based

Classification‟‟

Comparison of Early Stopping Criteria for

Shao, Y., Taff, G.N.and Walsh, S.J. (2011)

„„

*Energy Economics* **29**, 18-27.

market for oil?

‟‟

Are there exploitable inefficiencies in the futures

Shambora, W. E. and Rossiter, R. (2007)

„„

Subpixel

*Energy*

Modelling and Forecasting Petroleum Futures Vo

Sadorsky, P. (2006)

latility‟‟

„„

362.

*Processing: Explorations in Microstructure of Cognition. MIT Press, Cambridge, MA*, 1, 318-

*In: Rumelhart D E, McClelland J L et al. (eds.) Parallel Distributed*

by error propagation

‟‟

Learning internal representations

Rumelhart, D. E., Hinton, G. E. and Williams, R. J. (1986)

‟‟

*Energy Economics* **24**, 557-596.

the target zone model‟‟

An empirical exploration of the world oil price under

Tang, L. and Hammoudeh, S. (2002)

„„

*Press,* Cambridge, MA, A Bradford Book.

*The MIT*

Reinforcement Learning: An Introduction

Sutton, R. S. and Barto, A. G. (1998)

„„

„„

*Energy Policy* **23**, 861-870.

rmination of oil prices 1945-

1995‟‟

Stevens, P. (1995) „„The dete

*Letters* **8**(1), 113-117.

*Sensing*

*Remote*

*and*

*Geoscience*

*IEEE*

*International Forum on*

Model Based on Wavelet Transform and RBF Neural Network

‟‟

Crude Oil Price Forecasting with an Improved

Qunli, W., Hao, G. and Xiaodong, C. (2009)

„„

**18**(4), 431-444.

*OPEC Review*

How volatile are crude oil prices?

Plourde, A. and Watkins, G. C. (1994)

‟‟

„„

*Information Technology and Applications (IFITA '2009),* 231-234.

*Energy Report,* California Energy Commission.

price forecasts

‟‟

Results of Delphi VIII survey of oil

Nelson, Y., Stoner, S., Gemis, G. and Nix, H.D. (1994)

„„

6549-6553.

*Energy Policy* **35**,

Modelling Oil Price Volatility

Narayan, P. and Narayan, S. (2007)

‟‟

„„

*Psychological Review* **65**, 386-408.

organization in the brain

‟‟

The Perceptron: A probabilistic model for information storage and

Rosenblatt, F. (1958)

„„

952-955.

*(NAFIPS*

*’2001),*

*Proceedings of the Conference of the North American Fuzzy Information Processing Society*

*The*

markets

commodity

modelling

for

networks

neural

Fuzzy

(2001)

M.

Rast,

‟‟

„„

ert Approach: The LOPEX model‟‟

*International Advances in Economic Research* **8**, 324-334.

petroleum inventory

levels‟‟

Forecasting crude oil spot price using OECD

Ye, M., Zyren, J. and Shore, J. (2002)

„„

*Energy Economics* **24**, 107-119.

Volatility of the US Oil Market‟‟

An Analysis of Factors Affecting Price

Yang, C., Hwang, M. and Huang, B. (2002)

„„

*Energy policy* **34**(15), 2413-2428.

Hubb

Modelling long-term oil price and extraction with a

Xiong, T., Bao,Y. and Hu, Z. (2013)

„„

*Lecture notes in computer science* **3994**, 444-451.

b

ased on support vector machines‟‟

A new method for crude oil price forecasting

Xie, W., Yu, L., Xu, S. and Wang, S. (2006)

„„

*Enginners, Wester Electronic Show and Convention*, *Convention Record*, Part 4, 96-104.

*Radio*

„„

**4489**, 925-932.

*Lecture Notes in Computer Science*

based multiscale neural network learning paradigm

‟‟

Oil price forecasting with an EMD-

Yu, L., Lai, K. K., Wang, S. Y. and He, K. J. (2007)

„„

*Energy Economics* **26**, 783-799.

price formation‟‟

The empirical role of the exchange rate on the crude-oil

Yousefi, A. and Wirjanto, T. (2004)

*of*

*Energy Policy* **34**(17), 2736-2734.

low-i

nventory variables‟‟

short-run crude oil price using high- and

Ye, M., Zyren, J. and Shore, J. (2006)

„„Forecasting

*International Journal of Forecasting* **21**, 491-501.

relative inventories

‟‟

A monthly crude oil spot price forecasting using

Ye, M., Zyren, J. and Shore, J. (2005)

„„

price forecasting‟‟

A novel hybrid AI system framework for crude oil

Wang, S.Y., Yu, L. and Lai, K.K. (2004)

„„

*Journal of Systems Sciences and Complexity* **18**(2), 145-166.

methodology‟‟

with TEI@I

Crude oil price forecasting

Lai, K.K. (2005b)

L. and

Wang, S.Y., Yu,

„„

*Lecture Notes in Computer Science* **3327**, 233-242.

*Lecture Notes in Computer Science* **3327**, 233-242.

Oil Price Forecasting

‟‟

A Novel Hybrid AI System Framework for Crude

Wang, S., Yu, L. and Lai, K. K. (2005a)

„„

*Geophysics* **65**(4), 1032-1047.

Neural networks in geophysical applications

Van der Baan, M. and Jutten, C. (2000)

‟‟

*on Comparative Time Series Analysis,* Reading, MA: Addison-Wesley.

*Institute*

circuits

switching

Adaptive

(1960)

E.

M.

Hoff,

and

B.

Widrow,

‟‟

„„

„„

*Proceedings of the NATO Advanced Research Workshop*

Future and Understanding the Past

‟‟

Time Series Prediction: Forecasting the

Weigend, A. S., and Gershenfeld, N. A. (1994)

„„

*Energy Economics* **32**, 1477-1484.

Evidence Using GARCH-

class Models‟‟

Forecasting Crude Oil Market Volatility: Further

Wei, Y., Wang, Y. and Huang, D. (2010)

„„

View publication stats

View publication stats

*International Journal of Forecasting* **14**, 35-62.

The state of the art

‟‟

Zhang, G., Patuwo, B. E., and Hu, M. Y. (1998)

„„Forecasting with artiﬁcial neural networks:

„„

*Paper presented at the 6th IAEE European Conference,* Zurich, 2-3 September.

An Econometrics Forecasting Model of Short Term Oil Spot Price

Zamani, M. (2004)

‟‟

„„

*Energy Economics* **30**(5), 2623-2635.

neural network ensemble learning paradigm

‟‟

Forecasting crude oil price with an EMD-based

Yu, L., Wang, S. and Lai, K. K. (2008)