# A Hybrid Artificial Intelligence Approach to Monthly Forecasting of Crude Oil Price Time Series

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## Abstract

*Due to the important role of crude oil in the global economy, oil price is a key factor affecting economic plans and decisions of governments and commercial firms. Therefore, proactive knowledge of its future movements can lead to better decisions in various governmental and managerial levels. However, oil price forecasting with a satisfying accuracy has proved to be a difficult task because of the complex underlying mechanism governing oil price evolution. This paper proposes a hybrid artificial intelligence model for monthly crude oil price forecasting by means of feed-forward neural networks, genetic algorithm and k-means clustering. In order to evaluate the performance of the model, its forecasts are compared with those of the econometric model of Energy Information Administration as the best representative of econometric models, as well as three artificial intelligence models from the literature. Results show that our proposed model outperforms the above mentioned models.*

## 1. Introduction

Crude oil is one of the critical commodities in the world's economy, with its global supply and demand exceeding 80 million barrels per day and providing for almost two-thirds of global primary energy consumption along with natural gas [1].

While oil market participants are directly affected by the fluctuations of this market, there are also many other firms which make business decisions based on their expectations of crude oil price and hence are indirectly affected by these fluctuations. Furthermore, consumers are also affected by price inflation on consumer goods caused by rising oil price. Therefore, crude oil price forecasting has always been of considerable interest to many researchers and practitioners in academic institutions, commercial firms and governments.

Crude oil price is basically formed by supply and demand forces but extremely influenced by factors such as crude oil and petroleum products' inventory levels, gross domestic production, stock markets' activities, foreign exchange rates, political situation, market sentiments and even weather conditions at the same time [2-8]. These factors, among others, bring about a highly nonlinear and chaotic time-series for crude oil price [7, 9-11], which makes it rather difficult to capture the underlying mechanism for future forecasts.

Oil price forecasting approaches basically involve single- and multi-factor models. The former considers price lags as the only independent variable to forecast the future, while the latter includes other influential factors such as supply and demand as well. A variety of approaches, including statistical-based ones such as linear and non-linear regression, cointegration analysis, GARCH models, naive random walk (RW) predictors, vector auto-regression and error correction models, as well as artificial intelligence-based approaches such as artificial neural networks (ANN) and genetic programming (GP) are used both in single- and multi-factor domain. We now briefly review the literature on oil price forecasting.

Abramson and Finizza [12] used belief networks to produce forecasts. Gulen [13] used cointegration analysis to forecast West Texas Intermediate (WTI) price. Morana [14] adopted a forecasting approach based on GARCH properties of oil price. Kaboudan [15] employed GP and ANN to forecast refineries' acquisition cost (RAC) of crude oil. Tang and Hammoudeh [16] used non-linear regression to forecast OPEC basket price. Ye et al. [17-19] presented a simple econometric model of WTI prices using OECD petroleum inventory levels, and high- and low-inventory variables. Alvarez-Ramirez et al. [20, 21, 25] studied crude oil prices using multi-fractal analysis methods and chaos theory. Bernabe et al. [2]

developed stochastic multi-model approach to describe regime-switching in oil dynamics. Mirmirani and Li [22] used vector auto-regression and ANN to forecast U.S. oil price. Wang et al. [23] developed a hybrid AI framework by means of a systematic integration of ANN and rule-based expert system with web text mining. Yousefi et al. [24] used a wavelet based prediction. Lanza et al. [26] investigated crude oil and product prices using error correction models. Sadorsky [27] used different statistical to forecast daily volatility in petroleum futures price returns. Ghouri [3] showed that WTI price is inversely related to some of the petroleum products' stock levels. Dées et al. [28] described a structural econometric model of the world oil market. Shambora and Rossiter [29] predicted future prices of the crude oil with ANN. Amin-Naseri and Esfahanian [30] developed a two-layer feed-forward ANN (using 2 and 8 neurons with linear transfer functions in each hidden layer and 9 lags of oil price as inputs) to forecast monthly RAC. Gori et al. [31] considered three possible scenarios (parabolic, linear, and chaotic behavior of oil markets) to predict oil prices. Rehrl and Friedrich [32] generated long-term scenarios of future world oil supply and price up to the year 2100. Table 1 summarizes the literature on oil price forecasting.

**Table 1. Literature on oil price forecasting**

| Author(s) | Method |
|---|---|
| Abramson and Finizza | belief networks |
| Alvarez-Ramirez et al. | multi-fractals, chaos |
| Amin-Naseri and Esfahanian | ANN |
| Bernabe et al. | chaos |
| Dées et al. | structural econometric |
| Ghouri | linear regression |
| Gori et al. | regression, chaos |
| Gulen | cointegration analysis |
| Kaboudan | GP, ANN, RW |
| Lanza et al. | error correction |
| Mirmirani and Li | VAR, ANN |
| Morana | GARCH |
| Rehrl and Friedrich | long-term scenarios |
| Sadorsky | GARCH, TGARCH |
| Shambora and Rossiter | ANN |
| Tang and Hammoudeh | non-linear regression |
| Wang et al. | hybrid AI framework |
| Ye et al. | linear regression |
| Yousefi et al. | wavelets |

As can be seen from Table 1, most of the methods applied in the above mentioned papers belong to the range of statistical (and related) forecasting approaches. However, modeling the complex correlation between crude oil price and influential factors makes these methods quite difficult to use. Throughout the last two decades, a great deal of research has been devoted to using neural networks techniques especially in business and financial forecasting (see [33] as a comprehensive bibliography of researches regarding ANN applications in business). Peters [34] pointed out that most of the financial markets are not Gaussian-distributed but tend to have sharper peaks and fat tails. Under such evidence, a lot of traditional forecasting methods based on Gaussian normal assumption fall short compared to methods without these unrealistic assumptions. High capabilities of ANN in capturing non-linearity of today's volatile markets, e.g. oil markets, make it a promising choice in oil price forecasting [22, 29, 30]. Therefore, we will use ANN as a part of the proposed hybrid method in this paper.

One of the key findings explained by Peters [34] was that most financial markets have a long memory: "what happens today affects the future forever". In other words, current data are correlated with all past data to varying extents. The long-memory component of the market cannot be adequately explained by a system that works with short-memory parameters. Peters provided extensive evidence supporting his claim that markets have a fractal structure based on different investment horizons, i.e. they are not random in nature but consist of non-periodical cycles which are hard to detect and use in statistical or neural forecasting. He argues that financial markets are predictable, but accurate predicting algorithms need long memories.

Farmer and Sidorowich [35] found that chaotic time series prediction by local approximation is better than global approximation. Local approximation refers to the idea of breaking up the time domain into small neighborhoods and analyzing them separately. As an empirical study, Amin-Naseri and Soroosh [36] proposed a hybrid neural network for daily electrical peak load forecasting. They clustered the input data with self-organizing maps (SOM) and trained a feed-forward ANN for each cluster. The results indicated that the clustering approach significantly improved the forecasting results on individual ANN as well as on regression. Local approximation is used successfully by researchers in various forecasting fields such as stock prices, foreign exchange rates and general time series [37, 38, 39, 40].

Since oil price time series is a nonlinear long-memory series [2, 20, 21], it is a good candidate for application of local approximation techniques. However, no research in this topic has been seen (to the best of our knowledge) in the oil price forecasting literature. Researchers use various techniques to find local neighborhoods in these methods but k-means [36, 40] and SOM [39] are the most commonly used clustering techniques in this area. Therefore, we will cluster reconstructed state space of oil price time series using k-means clustering technique.

In designing neural network architectures, there are several factors such as number of layers, number of neurons in each layer, and transfer functions, which have considerable effects on the performance of neural networks. These factors are usually selected using the cumbersome and time-consuming procedure of trial and error with no justifications.

Genetic algorithm (GA) is a powerful technique in this context due to its ability to explore a vast region of solution space and exploit promising areas through genetic operations [41-45]. GA was specifically not employed in the oil price forecasting with ANN (to the best of our knowledge).

In this paper, we propose a hybrid ANN model which combines k-means technique to cluster the time series data and genetically-evolved feed-forward neural network to forecast oil price in the clustered data. The proposed model is compared to econometric as well as AI models to evaluate the effectiveness of the combination of various AI techniques used.

The rest of the paper is organized as follows. Section 2 presents description of the proposed hybrid ANN model. Empirical results and comparisons are reported in section 3. Finally, section 4 concludes the paper.

## 2. Proposed model

The proposed model consists of four main stages: data preparation, clustering, pattern matching and ANN design, and forecasting. The first stage prepares the time series of the respective oil price in order to be used in other stages. It includes data segmentation, determination of lags and state space reconstruction of each segment according to identified number of lags. Each point in the train/test state space is a train/test pattern.

The second stage takes training patterns as input, orthogonalizes the space and then clusters it. Each cluster is a group of similar patterns. The third stage matches each test pattern to the nearest cluster. Finally in the fourth stage, an ANN for each cluster is constructedand the test patterns matched to each cluster are tested on the respective ANNs to calculate forecasts. The following sub-sections explain these stages in detail.

### 2.1. Data preparation

In the first stage, a crude oil price time-series is considered. A segment of this time series is set aside for testing purposes while the rest will be used as training set. After segmentation of the dataset, Partial Autocorrelation Function (PACF) of the training time series is analyzed with 5% significance level to find the maximum number of lags (L) to be included as input in ANN model. Once L is specified, a sliding window of size L+1 is used to reconstruct the state space from training (and later in the process, testing) time series of crude oil price. Reconstructed state space of the training time series contains points resembling historical price patterns (simply, training patterns) whereas reconstructed state space of the test time series contains points resembling test price patterns (which their first L dimensions will be used in ANN to predict their respective targets – future prices). Figure 1 shows the process of applying a sliding window of size 5 (four lags and one target) on a typical time series.

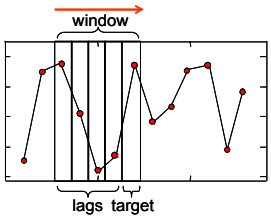


**Figure 1. Sliding window technique**

### 2.2. Clustering

In this stage, the training state space is clustered in order to group the training patterns so that the patterns in a cluster will be most similar ones and the patterns in different clusters will be most dissimilar ones. Well known k-means algorithm [36, 40] is used in the proposed model to cluster the state space. In order for clustering to be meaningful, data must be in orthogonal space. Principal component analysis (PCA) is applied to the state space to satisfy this requirement.

K-means needs the number of clusters to be specified. Since one has no a priori knowledge of this parameter, K-means is applied with number of clusters

from 2 to square root of the number of data points in the space. Minimization of the Davies-Bouldin index on the resulted clusters (for C=2,3,…,$\sqrt{N}$; where N is number of data points) suggests the best and hopefully inherent number of clusters present in the space. The Davies-Bouldin index is given in Equation 1:

$$\frac{1}{C}\sum_{k=1}^{C}\max_{l\neq k}\left\{\frac{S_c(Q_k)+S_c(Q_l)}{d_{ce}(Q_k,Q_l)}\right\} \quad (1)$$

in which $S_c$ represents within-cluster, $d_{ce}$ between-cluster distance, $Q_x$ the members of cluster $x$, and $C$ the number of clusters [39]. The proposed model uses k-means with this configuration: Euclidean distance, 1000 iterations until convergence and 100 replicates of algorithm to eliminate the effect of random initial starting points.

### 2.3. Pattern matching

This stage firstly reconstructs the state space of test series by a sliding window of size L+1, the same way as was done for training series. For each test pattern, the proposed model matches it to the nearest cluster in terms of Euclidean distance between that test pattern and the center of the cluster. Apparently, the last dimension of each test pattern belongs to the future and hence cannot be used in the forecasting process. So, this dimension is removed from test patterns. The Euclidean distances of this dimensionally reduced test pattern from all cluster centers are then measured to determine the nearest and hence the most similar cluster that we can match this pattern to.

### 2.4. ANN design and forecasting

This stage, firstly, utilizes GA to build an ANN for each cluster. The chromosome in the proposed model is a binary string containing 7 blocks: the first 3 blocks –$n_1$,$n_2$,$n_3$– denote the neurons in each hidden layer ($n_1$=[1,31],$n_2$=[0,31],$n_3$=[0,31]); the next 3 blocks –$f_1$,$f_2$,$f_3$– represent transfer functions in each hidden layer (1 for linear, 2 for log-sigmoid and 3 for tan-sigmoid) and "jc" is either 0 or 1 indicating jump connections from input to the output layer. Figure 2 shows the chromosome representing the ANN architecture.

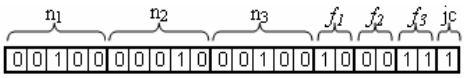


**Figure 2. Chromosome encoding**

Levenberg-Marquardt training function, gradient descent with momentum learning function and Nguyen-Widrow weight initialization are other architecture factors which we assumed fixed in our GA search for the best ANN architecture. The mean square error (MSE) function is used as the performance function. The Hannan-Quinn (HQ) information criterion is used in the GA algorithm as the fitness function (Equation 2),

$$HQ = T\log(MSE) + k\log(\log(T)) \quad (2)$$

in which $T$ represents the number of data points available in the respective cluster, $k$ denotes the number of connections in the network architecture (number of parameters used in the ANN model) and MSE shows the performance of the network after being trained on the respective cluster and reaching convergence. Note that the first L dimensions of each training pattern are introduced to ANNs as input and the last dimension is the desired target.

The GA configuration used in the proposed model is as follows: roulette wheel as for selection scheme, single-point crossover with a probability of 0.9, uniform mutation with a probability of 0.01, elite individuals equal to 1 in each generation, 50 members for each generation and 100 generations for convergence. GA implementation and required ANN training for chromosomes (in order to compute their fitness in each generation of GA) is done with the above mentioned parameter settings.

After finding the best ANN architecture for each cluster, the first L dimensions of each test pattern will be introduced into its respective ANN to produce forecasts. The forecasts will then be compared to the last dimension of each test pattern (i.e. the desired target) to compute forecasting performance. Stages of the proposed model are shown in Figure 3.

## 3. Empirical results

Having explained the steps of the proposed model, we now execute the model to forecast the oil price in a variety of datasets. In order to provide a fair base for performance evaluation of our proposed model to some competing models, the datasets were chosen in a way that other competing models experienced them.

The selected competing models are as follows: 1) short-term energy outlook (STEO) model of Energy Information Administration in U.S. Department of Energy [1] as the best representative of econometric models; 2) the genetic programming model of Kaboudan (KAB) which was shown superior to other models by Kaboudan [15], as a good AI model; 3) AI framework of Wang et al. (WANG) [23] which extensively used AI techniques such as ANN, rule-

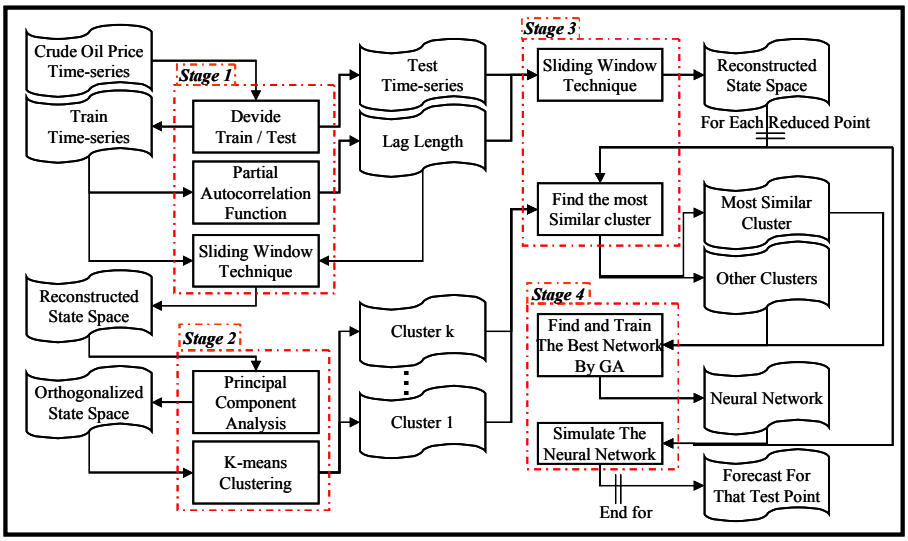


**Figure 3. The Proposed model**

based expert system and web-based text mining, as another good AI model; and 4) ANN model of Amin-Naseri and Esfahanian (AMIN) [30] as an extensive trial and error ANN model. Another reason for choosing these models for comparison is that the oil price data they have used are available and that their forecasts show to be superior to other models. Concerning STEO, the oil price dataset from January 1983 to December 2006 (288 datapoints) for WTI is extracted from EIA website. It should be mentioned that STEO provided its forecasts for the last 15 months. Hence, out of these 288 data points, the last 15 observations were selected as test dataset in the first experiment. In the second experiment, RAC data (used by Kaboudan) from January 1974 to December 1998 (300 months) are used for training set and the data for year 1999 (12 months) for testing set. In the third experiment, WTI oil prices from January 1983 to December 1999 (204 months) are used for training set and prices of years 2000-2002 (36 months) for testing set. The fourth experiment uses RAC data from January 1974 to October 2000 (322 months) for training set and data from November 2000 to December 2001 (14 months) for testing set. Various features of the experiments are summarized in Table 2.

**Table 2. Experiments Features**

| Features \ Experiments | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Competing model | STEO | KAB | WANG | AMIN |
| Crude oil | WTI | RAC | WTI | RAC |
| Training range | 01/1983<br>09/2005 | 01/1974<br>12/1998 | 01/1983<br>12/1999 | 01/1974<br>10/2000 |
| # Train observations | 273 | 300 | 204 | 322 |
| Test range | 10/2005<br>12/2006 | 01/1999<br>12/1999 | 01/2000<br>12/2002 | 11/2000<br>12/2001 |
| # Test observations | 15 | 12 | 36 | 14 |

Results of the model construction including number of lags determined by PACF, best number of clusters suggested by Davies-Bouldin index on clustering results of k-means, number of test patterns matched to each cluster and the best ANN architecture for each cluster in experiments 1-4, are reported in Table 3. As can be seen in this table, usually a few hidden neurons are used in each layer, leading to parsimonious networks which have better generalization capability. Also jump-connections exist between input and output output layers which indicate the linear relationship between input and output of the network.

**Table 3. Results of model construction**

| Results of model construction \ Experiments | | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| # Lags | | 10 | 15 | 15 | 15 |
| # Clusters | | 3 | 2 | 2 | 2 |
| # Test patterns matched to… | Cluster 1 | 15 | 0 | 5 | 1 |
| | Cluster 2 | 0 | 12 | 31 | 13 |
| | Cluster 3 | 0 | × | × | × |
| ANN architecture of…* | Cluster 1 | [3-8-2] [T-T-T] "on" | × | [2-8-1] [P-T-T] "on" | [3-8-2] [T-T-T] "on" |
| | Cluster 2 | × | [3-5-1] [L-L-L] "on" | [5-3] [T-T] "on" | [1-7] [T-T] "on" |
| | Cluster 3 | × | × | × | × |

* ANN architecture is denoted by [n1-n2-n3],[f1-f2-f3],"jc"; P is for pure linear, T for tan-sigmoid and L for log-sigmoid transfer function.

Table 4 provides performance criteria needed for the comparison of the proposed model versus competing models in each experiment. Nine different criteria were used for comparison.

As for mean absolute error (MAE), mean absolute percentage error (MAPE), sum of square errors (SSE), mean square error (MSE), root mean square error (RMSE), U2-Theil (ratio of model RMSE to the random walk RMSE) and $R^2$ performance criteria, the proposed model is shown to be superior to other models. The only shortages occur in the third and fourth experiments.

Directional accuracy (DA) which means the percentage of times that a model can correctly forecast the direction of movements is less than WANG in the third experiment. Note that WANG uses text-mining in oil news as a means to adjust its raw ANN forecasts (which may be a reason to explain the superiority of WANG in this particular criterion). Particularly note that the proposed model outperforms other models in terms of DA criterion by a relatively large factor. It should be noted that WANG did not report any information regarding to some criteria which are marked by "×" in Table 4.

In the fourth experiment, maximum absolute error (MaxAE) criterion of AMIN is less than that of the proposed model only by 0.5%.

Altogether, it can be said that the proposed model outperforms other models from oil price forecasting experiments.

**Table 4. Results from comparisons of the proposed model to the competing models**

| Performance Criteria | Experiment 1 | | Experiment 2 | | Experiment 3 | | Experiment 4 | |
|---|---|---|---|---|---|---|---|---|
| | STEO | Proposed | KAB | Proposed | WANG | Proposed | AMIN | Proposed |
| MAE | 2.36 | **2.29** | 1.15 | **0.79** | × | 1.61 | 1.54 | **1.28** |
| MAPE | 3.7% | **3.6%** | 7.8% | **4.9%** | × | 5.9% | 6.9% | **5.6%** |
| Max AE | 7.20 | **5.97** | 2.53 | **2.02** | × | 3.52 | **4.34** | 4.45 |
| SSE | 138.7 | **136.5** | 22.1 | **10.8** | × | 133.4 | 46.9 | **37.2** |
| MSE | 9.25 | **9.10** | 1.84 | **0.90** | 5.61 | **3.71** | 3.35 | **2.66** |
| RMSE | 3.04 | **3.02** | 1.36 | **0.95** | 2.37 | **1.92** | 1.83 | **1.63** |
| DA | 73% | **80%** | 75% | **83%** | **81%** | 78% | 57% | **71%** |
| U2-Theil | 0.73 | **0.725** | 0.90 | **0.63** | × | 0.88 | 0.91 | **0.81** |
| $R^2$ | 0.667 | **0.672** | 0.92 | **0.96** | × | 0.72 | 0.72 | **0.78** |

## 4. Summary and conclusion

Due to the important role of crude oil in the global economy, oil price is a key factor affecting economic plans and decisions of governments and commercial firms. Therefore, proactive knowledge of its future movements can lead to better decisions in various governmental and managerial levels. Oil price forecasting is very complex because it is a highly volatile, non-linear and chaotic financial time series.

In spite of efforts devoted to solve this problem using various statistical-based methods, oil price forecasting remains a hard-to-solve problem because of its intrinsic difficulty, seemingly unpredictable nature and various factors affecting oil market fluctuations.

The review of crude oil price forecasting literature shows that limited number of researches has been devoted to AI domain methods. Particularly use of local approximation techniques (to cluster similar datasets) and GA (to find the best neural network architecture) have not been investigated in this context.

In this paper, we proposed a hybrid ANN model for crude oil price forecasting which exploits local approximation techniques by using k-means clustering (to find local neighborhoods in the state space of the time series). The genetic algorithm was used to construct the best architecture for artificial neural networks for each cluster.

To evaluate the performance of the proposed model, four competing models namely STEO, KAB, WANG, and AMIN (which had considerable experiences in oil price forecasting) were chosen for comparison. In order to provide a fair base for comparison, the datasets were chosen in a way that other competing models experienced them with their own models. Therefore, we implemented four different experiments to compare the results of the proposed model to the four competing models with respect to nine performance criteria.

The first experiment compared the proposed model to STEO, which is a huge econometric model developed by Energy Information Administration in U.S. Department of Energy as the best representative of econometric approaches. Results of this experiment on WTI crude oil price forecasting showed that the proposed model outperforms STEO in terms of all nine performance criteria. The second experiment (comparison with KAB) proved the superiority of the proposed model in all criteria, too. With regard to experiment 3, our proposed model resulted in better forecasts with respect to two (out of three) of the criteria reported by WANG. Finally the fourth experiment compared the proposed model with AMIN, in which significant improvements in all performance criteria (but MaxAE) proved the superiority of the proposed model.

In general, it can be said that the introduction of local approximation techniques in crude oil price time series forecasting, combined with genetically-evolved neural networks has proven to be successful.

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