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Full Length Research Paper

A hybrid optimized artificial intelligent model to forecast crude oil using genetic algorithm

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Crude oil is one of the most critical energy commodities while with coal and natural gas are projected to provide roughly the 86% share of the total US primary energy supply in 2030. In this study, a novel hybrid optimum model based on artificial intelligent (AI) is proposed for world crude oil spot price forecasting. A three-layer feed forward neural network (FNN) model was used to model the oil price forecasting. Genetic algorithm (GA) is employed not only to improve the learning algorithm, but also to reduce the complexity in parameter space. GA optimizes simultaneously, the connection weights between layers and the thresholds. In addition, GA reduces the dimension of the feature space and eliminates irrelevant factors. For verification and testing, two main crude oil price series, West Texas intermediate (WTI) crude oil spot price, Brent crude oil spot price and Iran crude oil are used to test the effectiveness of the proposed optimized neural network. Results show that optimized model has advantages in comparison with conventional ANN in terms of accuracy, variability, model creation and model examination. Both simulated and actual data sets are used for comparison.

Key word: Artificial neural network, crude oil, genetic algorithm, optimization.

INTRODUCTION

Crude oil has been playing an increasingly important role in the world economy since nearly two-third of the world's energy demands is met from crude oil (Alvarez-Ramirez et al., 2003). Yu et al. (2008) said that crude oil is also the world's largest and most actively traded commodity, accounting for over 10% of total world trade.

Watkins (1994) introduced the factors like weather, stock levels, GDP growth, political aspects and even people's psychological expectations lead to a strongly fluctuating crude oil market, which has the characteristics of complex nonlinearity, dynamic variation and high irregularity. In addition, as sharp oil price movements can disturb aggregate economic activity, crude oil price fluctuations may have a significant impact on a nation's economy. From the different perspectives, sharp increases in crude oil prices adversely influence economic growth and accelerate inflation for oil importing economies. Abosedra and Baghestani (2004) showed a fall in crude oil prices, like the one in 1998, will generate serious budgetary deficit problems for oil exporting countries.

In the past decades, traditional statistical and econometric techniques such as linear regression, co-integration analysis, GARCH models, naive random walk, vector auto-regression (VAR) and error correction models (ECM) have been widely applied to crude oil price forecasting. For example, Huntington (1994) applied a sophisticated econometric model to predict crude oil prices in the 1980s. Abramson and Finizza (1995) utilized a probabilistic model for predicting oil prices, and Morana (2001) suggested a semi-parametric statistical method for short-term oil price forecasting based on the GARCH properties of crude oil price. Similarly, Barone-Adesi (1998) suggested a semi-parametric approach for oil price forecasting. Gulen (1998) used co-integration analysis to predict the West Texas intermediate (WTI) price.

Ye et al. (2002, 2005, 2006) presented a simple econometric model of WTI prices, using OECD petroleum inventory levels, relative inventories, and high- and low-inventory variables. Mirmirani and Li (2004) used the VAR model to predict U.S. oil price. Lanza et al. (2005)

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investigated crude oil and oil product's prices using error correction models (ECM).

Usually, the mentioned models can provide good prediction results when the price series under study is linear or near linear. However, in real-world crude oil price series, there is a great deal of nonlinearity and irregularity. Numerous experiments have demonstrated that the prediction performance might be very poor if one continued using these traditional statistical and econometric models (Weigend and Gershenfeld, 1994). The main reason leading to this phenomenon is that the traditional statistical and econometric models are built on linear assumptions and they cannot capture the nonlinear patterns hidden in the crude oil price series.

Due to the limitations of the traditional statistical models, some nonlinear and artificial intelligent (AI) models, such as nonlinear regression, artificial neural networks (ANN), support vector machines (SVM) and genetic programming (GP), provide powerful solutions to nonlinear crude oil price prediction. For example, Abramson and Finizza (1991) used belief networks, a class of knowledge-based models, to forecast crude oil prices. Kaboudan (2001) employed GP and ANN to forecast crude oil price. Tang and Hammoudeh (2002) proposed a nonlinear regression model to forecast OPEC basket price. Shambora and Rossiter (2007) and Yu et al. (2007) also used the ANN model to predict crude oil price. Many experiments found that the AI-based models often had some advantages over statistical-based models.

Most studies showed that ANN had some limitations in learning the patterns because cost data has tremendous noise and complex dimensionality. Liu (1996) discussed that ANN has preeminent learning ability while it is often confronted with inconsistent and unpredictable performance for noisy data. In addition, sometimes, the amount of data is so large that the learning of patterns may not work well.

This paper proposes a new hybrid model of ANN and genetic algorithm (GA) for model optimization. Proper data reduction can simplify the process of learning and may improve the performance of the learned results. This study uses GA to search the optimal or near-optimal the connection weights between layers and thresholds in ANN. The simulation results show that the performance of optimized model is higher than conventional ANN. In addition, model creation will be easier and faster.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are a class of typical intelligent learning paradigm, widely used in some practical application domains. In this study, a standard three-layer feed-forward neural network (FNN), based on error back-propagation algorithm, is selected for modeling the crude oil price variation.

Usually, a FNN-based forecasting model can be trained by the in-sample dataset and applied to out-of sample dataset for prediction. The model parameters (connection weights and node biases) are adjusted by a process of minimizing the forecasting error function. Basically, the final output of the FNN based forecasting model can be represented as:

$$f(x) = a_0 + \sum_{j=1}^{q} w_j u(a_j + \sum_{i=1}^{p} w_{ij} x_i) \quad (1)$$

$$x_t = \varphi(x_{t-1}, x_{t-2}, ..., x_{t-p}, w) + \zeta_t \quad (2)$$

where $x_i (i = 1,2,..., p)$ represents the input patterns, $f(x)$ is the output, $a_j (j = 0,1,2,..., q)$ is a bias on the j_{th} unit, and w_{ij} $(i = 1,2,..., p; j = 0,1,2,..., q)$ is the connection weight between layers of the model; φ is the transfer function of the hidden layer, p is the number of input nodes, q is the number of hidden nodes, w is a vector of all parameters and φ is a function determined by neural network training.

The main reason of selecting FNN as a predictor is that it is often viewed as a universal approximator. White (1990) found that a three-layer feed-forward neural network (FNN) with an identity transfer function in the output unit and logistic functions in the middle layer units can approximate any continuous function arbitrarily well, given a sufficient amount of middle layer units. That is, neural networks have the ability to provide a flexible mapping between inputs and outputs. While theoretically, in universal approximations, there are practical problems in neural network model construction and validation when dealing with stochastic relationships, or noisy, sparse or biased data, most studies showed that ANN had some limitations in learning the patterns because cost data has tremendous noise and complex dimensionality. Liu (1996) discussed that ANN has preeminent learning ability while it is often confronted with inconsistent and unpredictable performance for noisy data. In addition, sometimes the amount of data is so large that the learning of patterns may not work well.

GENETIC ALGORITHM APPROACH

Goldberg (1989) and Holland (1992) introduce the GAs such as search techniques based on an analogy with biology in which a group of solutions evolves through natural selection. In their implementation, a population of randomly generated candidate solutions evolves to an optimum solution through the operations of genetic operators consisting of reproduction, crossover and mutation.

A standard GA approach for searching the optimal or

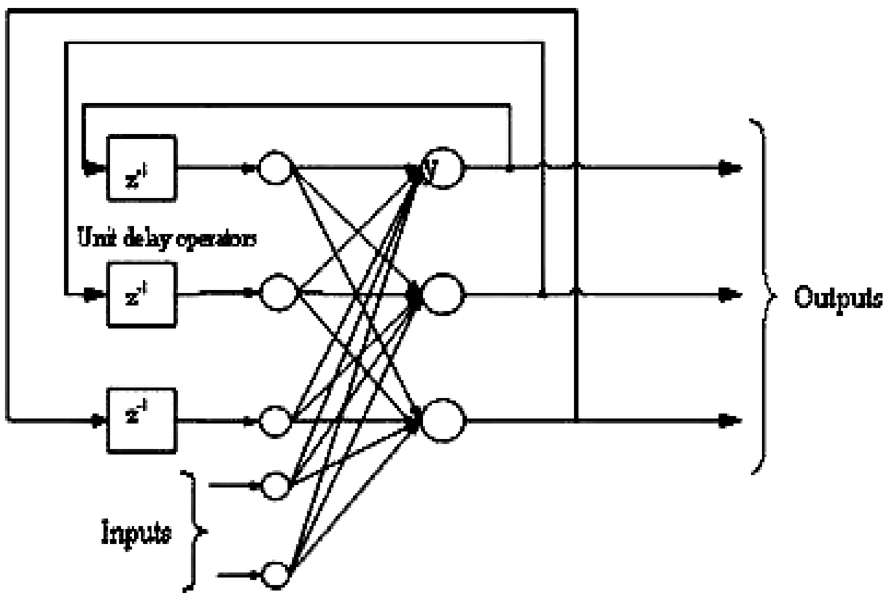

Figure 1. The back propagation neural network.

near optimal connection weight in ANN model for cost estimation problem is described here. The principal components of the optimization based on standard GA are given thus:

(i) Chromosomes: A chromosome can be taken as an array holding a candidate optimization. The connection weights and thresholds are set as elements in the chromosomes.
(ii) Fitness function: This is the evaluation function used to calculate the degree of fitness or appropriateness of the candidate solutions. The following fitness function can be used:

$$F = \frac{M}{10^{-5} + H} \quad (2)$$

where M is a constant for amplifying the fitness value. The value of H approaches zero towards convergence. To avoid any numerical difficulty that may occur in calculating F and H is augmented by 10^{-5}.
(iii) Crossover operation: This is a genetic operation which is responsible for producing two new candidate solutions from two selected parent chromosomes.

Booker (1987) proves that in the present working, the two-point crossover method is adopted so that more diversity in the population of chromosomes can be achieved. In this method, two numbers within the length of the chromosome are randomly generated. The elements between the two numbers in the two parent chromosomes are swapped to form two new chromosomes.
(iv) Mutation operation: An element of a chromosome is randomly selected. The voltage value of the element is replaced by a value arbitrarily chosen within a range of voltage values.

Using the afore listed components, a standard GA procedure for solving the load flow problem is summarized thus:

Step 1: Initialize S chromosomes in the population. The elements of a chromosome are the candidate modal described in the listed item (i)
Step 2: Generate the next generation of S chromosomes in the following way:
Step 3: The next generation formed in step 2 is now taken to be the current generation. New generations are produced by repeating the solution process starting from step 2 until the specified maximum number of generations is reached.

FORECASTING CRUDE OIL PRICE USING HYBRID AI MODEL

In this study, two main crude oil price series, West Texas intermediate (WTI) crude oil spot price and Iran crude oil spot price are chosen as experimental samples. The main reason for selecting these two oil price indicators is that different factors can affect on them.

This paper uses a three-layer neural network which is trained by using the error back propagation (BP) algorithm which is shown in Figure 1 as a conventional model. The number of neurons in the layers, termed as input layer, hidden layer and output layer, are determined by experimentation with an object that the ANN learns and generalizes the situation.

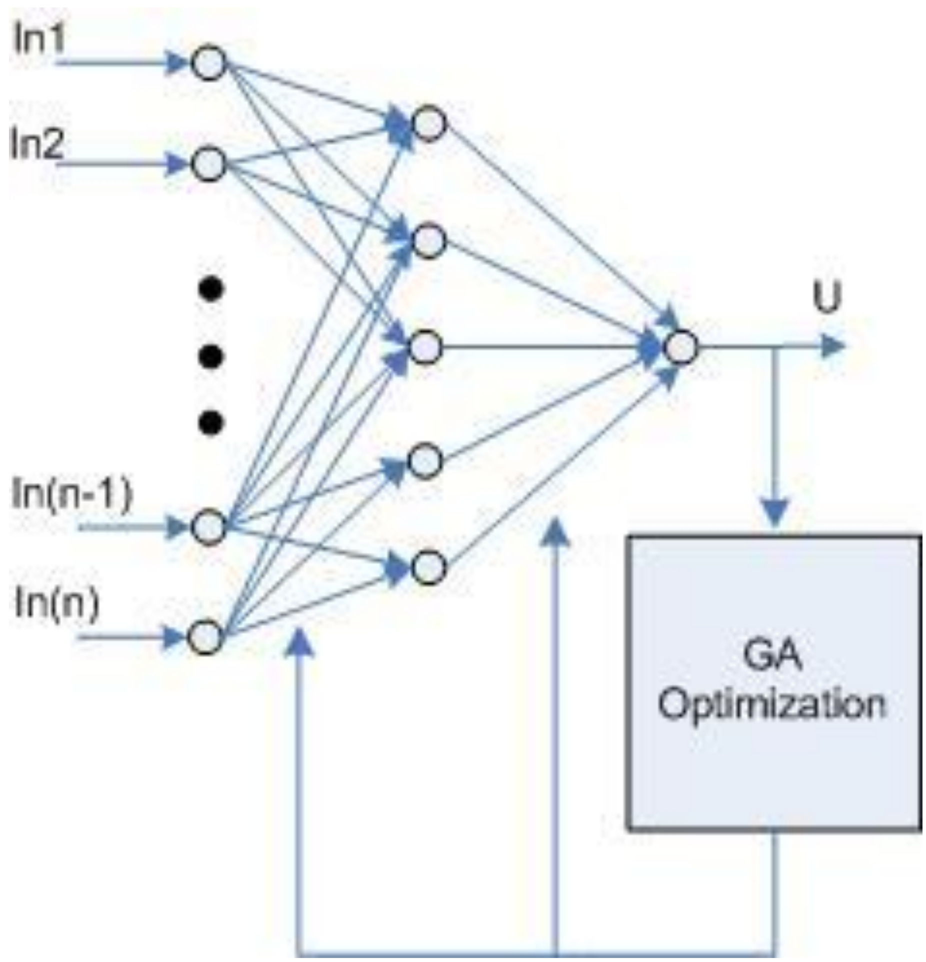

Figure 2. The optimized neural network.

Table 1. Definition of the auxiliary parameters.

R	Auxiliary parameters	Definition
1	TP	The number of positive class predicted correctly as positive class
2	FP	The number of negative class predicted wrongly as positive class
3	FN	The number of positive class predicted wrongly as negative class
4	TN	The number of negative class predicted correctly as negative class

In this paper, linear transformation with the back propagation neural network (BPLT) and the linear transformation with ANN trained by GA is simulated using Matlab software. The neural network with genetic algorithm optimization is shown in Figure 2.

The study defined four auxiliary parameters to calculate the performance of each model. Daniel Ramirez (2002) introduces auxiliary parameters which are shown in Table 1. To compare the performance of the models, the study calculates the following parameters:

$$A=(TP+TN)/(TP+FP+TN+FN) \quad (8)$$

$$P=TP/(TP+FP) \quad (9)$$

$$R=TP/(TP+FN) \quad (10)$$

where A is accuracy, P is precision and R is recall rate or sensitivity.

Two models are compared according to the methods of determining the connection weights and feature transformation. Figure 3 and 4 shows the outputs of two models in comparison with actual WTI and Ian light monthly oil price respectively. Output data of optimized

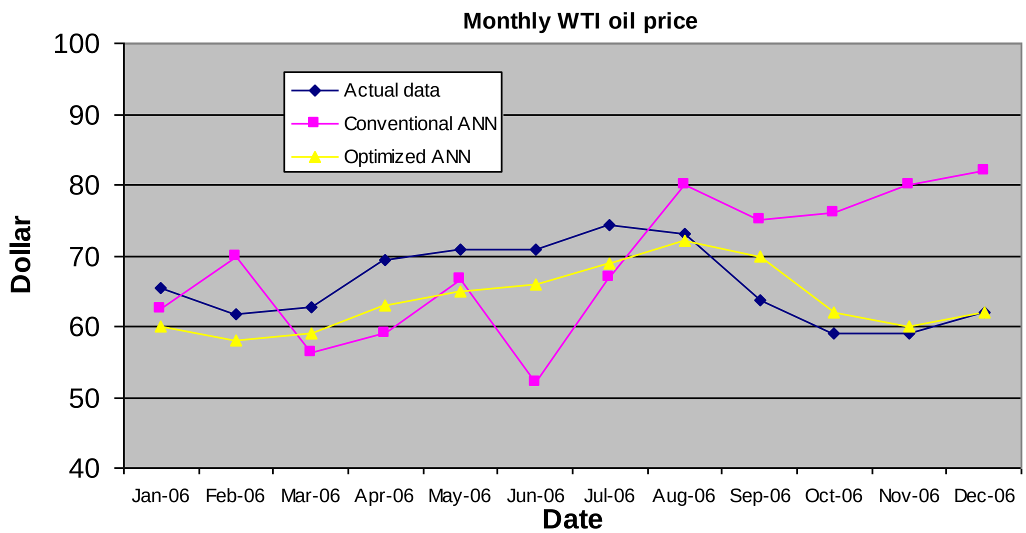

Figure 3. Comparison between conventional and optimized model to estimate WTI monthly price.

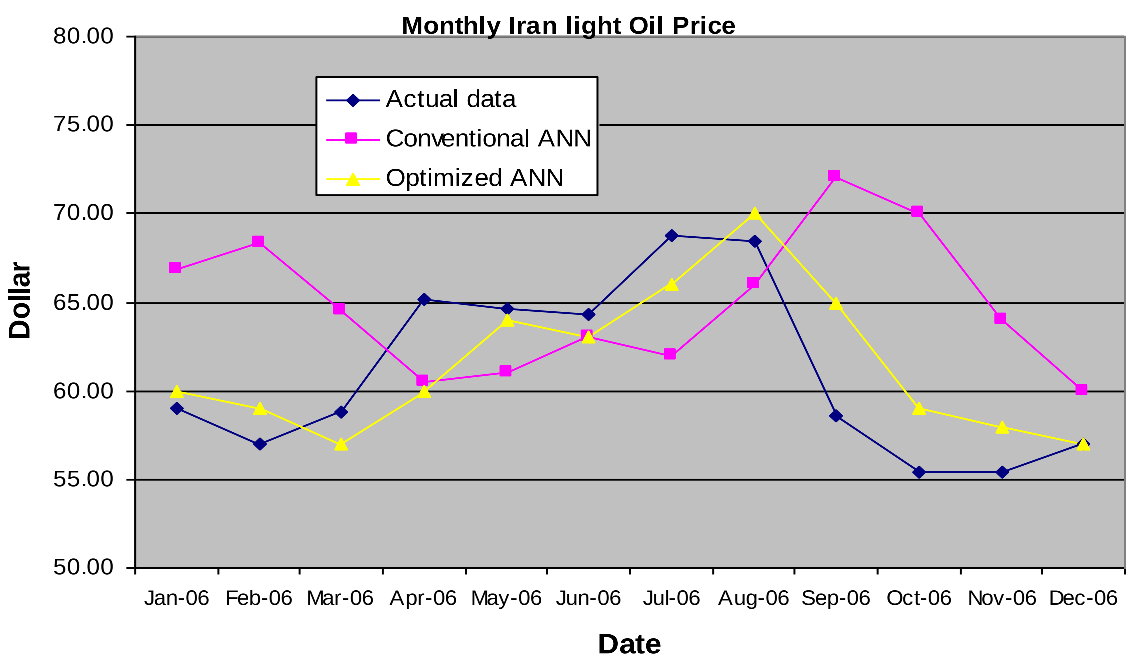

Figure 4. Comparison between conventional and optimized model to estimate Iran light oil monthly price.

model is more reliable and close to actual prices.

Table 2 describes the average prediction accuracy of each model for WTI and Iran light oil spot prices. The optimized model has higher prediction accuracy than conventional model by 8 to 11% for the training data.

CONCLUSION

In this paper, a hybrid optimized neural network model to forecast crude oil has been proposed and simulated. GA optimizes simultaneously, the connection weights between layers and the thresholds. In addition, GA reduces the dimension of the feature space and eliminates irrelevant factors. West Texas intermediate (WTI) crude oil spot price and Iran light crude oil spot price from 1994 until 2008 are chosen as experimental samples. Sixty percent of data has been used to train the ANN and another has been used to test the model. The prediction results of optimized model have more fitness and precision in comparison with conventional model. close to actual prices.

Table 2. Comparison between precision of output model in the year.

Date	WTI conventional model (%)	WTI optimized model (%)	Iran light oil conventional model (%)	Iran light oil optimized model (%)
1995	62.2	78.2	54.3	73.3
1996	66.4	72.3	44.6	68.4
1997	55.6	66.7	49.7	66.9
1998	67.1	75.5	62.3	72.1
1999	56.3	70.3	55.3	64.5
2000	42.5	71.2	64.8	69.8
2001	55.2	65.5	66.3	67.3
2002	59.9	66.8	69	63.2
2003	66.3	60.3	49.3	68.4
2004	63.5	72.3	44.8	59.7
2005	57.4	71.1	54.9	64.5
2006	65.5	67.3	49	58.2
2007	54.4	69.9	45	61.2

Output data of optimized model is more reliable and

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