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OPEC Oil Price Prediction Using ANFIS

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Abstract

In this paper adaptive neuro-fuzzy inference system (ANFIS) is developed to predict the oil prices of the organization of petroleum exporting countries (OPEC). The novel aspect of the proposed model is the proposed features set fed the ANFIS. In the numerical studies, the proposed method is tested to modeling OPEC oil time series as a case study. According to the comparative results, ANFIS with proposed variables set shows higher accuracy than conventional neural networks in oil price prediction.

Keywords: Artificial neural network; Fuzzy; Oil; Forecasting.

1. Introduction

Recently a scientific issue, related to the oil price prediction, has been considered by artificial intelligence (AI) researchers and economic analyzers (Knetsch 2007; Shafiee & Topal 2010; Shin et al. 2012). Generally there are two approaches to this issue, including mathematical models and Artificial Intelligence (AI) methods. Mathematical models include VAR (Alquist and Kilian 2010), kalman filter (Bhar and Lee 2011) ARMA (Karia et al. 2013), ARCH and GARCH etc. (Morana, 2001; Sadorsky 2002; Yaziz *et al.*, 2011; Baumeiste & Kilian 2012; Deepika et al. 2012; Gibson and Schwartz 1990). And AI methods consist of learning based methods such as Artificial Neural Network (ANN; Lotfi and Navidi 2012; Mehdi Sotoudeh and Elahe Farshad 2012; Ali ghezelbash 2012; Hamze Ravaee et al. 2012; Lachtermacher and Fuller 1995; Moshiri, & Cameron 2000; Haidar and Kulkarni 2008; Malliaris and Malliaris 2009, 2013; Anand *et al.*, 2010; Mustaffa and Yusof, 2011; Mingming, 2012; Wang and Pan 2012; Parisi et al. 2008; Khashei et al. 2009) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS; Atsalakis, 2012; He *et al.*, 2012; Makridou et al. 2013). AI methods learn behavior by observing the previous values and predict the future values. The learning based methods are more accurate in economic time series prediction and among AI methods, ANFIS can show better results. Recently, Chen et al. (2014) show ANN is a better predictor that ARIMA model for forecasting gold price and Yazdani et

al. (2012) show that ANFIS is the more appropriate than mathematical models and ANN. They have utilized CAM (cosine amplitude method; Yazdani et al. 2012) method to identify the most sensitive factors affecting gold price. CAM is not suitable for sensitivity analysis of economic time series, because it does not include behavioral similarities of time series. This paper aims to apply ANFIS in OPEC oil price time series prediction. ANFIS successfully learn the behavior and can be used for prediction and estimation and we believe that because high accuracy, it can be applied to find the sensitivity of economic parameters. Here we apply ANFIS for prediction of non-stationary chaotic economic time series of oil as a case study. The proposed model is general and can be applied in various economy based application domains such as product cost estimation (Smith & Mason 1997; Liu 2010), stock price prediction (Ince and Trafalis 2007, 2008; Thawornwong, S., Enke and Dagli 2003), exchange rate detection (Sarantis & Stewart, 1995; Akram 2004; Knowles et al. 2005; Alvarez-Diaz & Alvarez 2007; Dunis et al. 2010; Amirhosseini & Behbahani 2011; Ebrahimpour et al. 2011), inflation forecasting (Monteforte and Moretti 2013, Choudhary & Haider 2012), forecasting different commodity prices (Chinn and Coibion 2013) as well as gas consumption and various demand functions estimation (Darbellay & Slama 2000; Gorucu 2004; Çunkaş & Altun2010; Azadeh et al. 2010).
The organization of the paper is as follows: ANFIS based modeling is presented in Section 1.1. Oil price prediction, is presented in Section 2. The method is evaluated in the Section 3 and conclusions are made in Section 4.

1.1. ANFIS based modeling

ANFIS is a Neuro-Fuzzy approach introduced by Jang (Jang et al. 1997, 1993), explored by Takagi and Sugeno (1985) and utilized in various control applications, prediction and inference. ANFIS is a fuzzy inference system that trains their learning parameters in ANN architecture. A fuzzy system transmits expert knowledge expressed by linguistic rules into a mathematical framework and ANFIS adjusts these rules using ANN architecture. In other words, ANFIS is a solution that combines fuzzy systems and ANN and uses the advantages of them where the fuzzy rules and membership functions are generated automatically.
In Sugeno-type ANFIS, the rules can be obtained by subtractive clustering (subclust). The subtractive clustering (Chiu 1994; Yager and Filev 1994) is used to determine the number of rules and antecedent membership functions. Also the linear least squares estimation is applied to determine each rule's consequent equations. This method is implemented in Matlab function “subclust” and applied in function “genfis2”. The subclust uses a cluster center's range of influence (radii) in each of the data dimensions. Small ranges generally results a few large clusters and big ranges results many little clusters. These ranges can be tuned separately and manually for each problem. Here, membership functions are Gaussian (*gaussmf*), output membership function is linear and a manual optimum radius is proposed for each case study. In inference method, AND is *prob*, OR is *probor*, implication is *min* and aggregation is *max* and defuzzification method is weighted average (*wtaver*).

2. Oil Price Prediction

Oil bear great importance on economic markets and their prices play pivotal role in the global economy. These prices can be considered as economic time series showing non-stationary, non-linear chaotic behavior and high uncertainty (Elder and Serletis 2010). Recently various predictor models have been utilized by researchers and analysts to predict oil prices. An accurate predictor can help to foresee the circumstances of trends in the future (Yazdani-Chamzini et al. 2012) and provide the useful information for customers, suppliers, politicians and generally for stakeholder to fulfill the appropriate strategies in order to prevent or mitigate risks (Yazdani-Chamzini et al. 2012). These prices are very difficult to forecast (Coimbra and Esteves 2004). So in the literature, the predictors have been investigated in order to find the best predictor. As mentioned above, ANFIS can show better result in prediction and we apply it as follows:

At the first, Let us list the affecting parameters on the oil prices. As mentioned in the published papers, there are various parameters that affect oil prices such as OPEC (The Organization of Petroleum Exporting Countries) production level, inflation rate, interest rate, gold and silver prices, global economy as well as imports of major purchaser countries such as USA (Hamilton 2009; Nashawi *et al.* 2010). These parameters can be considered as inputs of ASFIS where its output is oil price. The list of parameters considered here are shown in Table 1. These parameters are used as shown in Fig. 1. Fig. 1 shows the ANFIS based oil price predictor that has two sets of input variables: First set is the parameters under consideration presented in Table 1 and the second set is the oil prices of three previous periods including Op_{i-1}, $Op_{i-2,}$ andOp_{i-3}. The output of ANFIS is the predicted oil price for current period i (Op_i). The proposed input variables for ANFIS model is a novel aspect presented here. Published works such as (Yazdani et al. 2012) have not considered previous values of time series beside other parameters. Additionally we find that the best radii = [0.52 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5] is obtained for oil price prediction.

Table 1. Economic variables under consideration for prediction

	Input Variable	**Unit**	**Symbol**	**Source**
1)	US Inflation rate	-	Inf	http://inflationdata.com
2)	Interest rate	-	Int	http://www.EconStats.com
3)	OPEC oil production level	Thousand Barrels Per Day	Opl	http://tonto.eia.gov
4)	Gold Price	$/ounce	Gp	http://www.gold.org
5)	Silver Price	$/ounce	Sil	https://www.silverinstitute.org
6)	Market Index	$	Dji	http://finance.yahoo.com
7)	U.S. Dollar Index	-	Din	http://research.stlouisfed.org
8)	Oil price (USA F.O.B. cost of OPEC)	Dollars per Barrel	Op	http://tonto.eia.gov

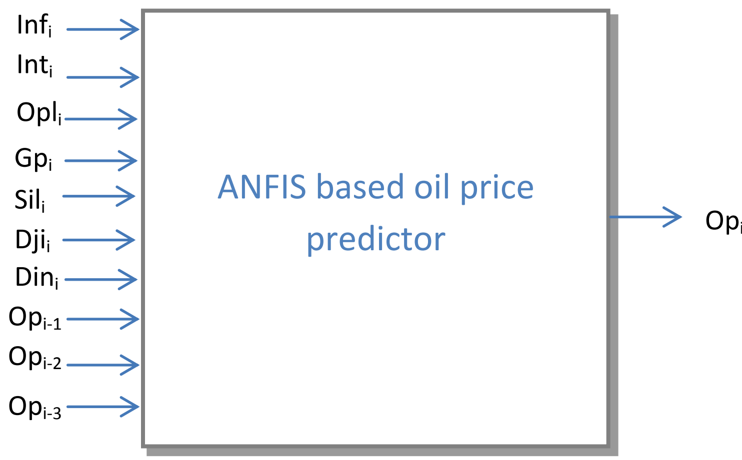

Fig. 1. Inputs and output of ANFIS as oil price predictor

3. Numerical results in price prediction

A 136 monthly samples data set from Sep. 2001 to Dec. 2012 has been used for prediction. The data sets are accessible from sources presented in Table 1. The monthly data from Sep. 2001 to Nov. 2009 are used for ANFIS training, from Dec. 2010 to Dec. 2012 are used for testing and the remaining set is the validation set. In experimental studies, the measures are the size of error, the root mean squared error (RMSE) and the correlation coefficient (COR).

Fig. 2 presents the oil prediction results and the related error obtained from ANFIS. In Fig. 2, the training region is between months [Sep-2001 Nov-2009]and months [Dec-2010 Dec-2012] are for the testing where the prediction results are evaluated. The validation set is used to find the best radii that is [0.52 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5]. As illustrated in Table 2, in *Op* prediction, a correlation COR = 0.98470 and test RMSE = 22.3565 are obtained. We use this dataset to do some experiments to examine performance of ANFIS and compare it with performance of an ANN model. We consider Levenberg-Marque (LM) learning based ANN with at least five different structures (single layer with 5, 10, 15, 20, and 25 neurons in the hidden layer). For each network, experiments are repeated 10 times on validation set. The obtained validation set RMSE for 5, 10, 15, 20, and 25 hidden neurons are 6.240000716 ± 4.682317126, 8.015831731 ± 3.742401937, 9.181441105 ± 3.305491527, 7.743900664 ± 2.798479512 and 16.06593922 ± 5.027978399 respectively. Thus the best ANN architecture for oil price forecasting is 10-5-1 (10 input features, 5 hidden neurons and 1 output.) Table 2 shows the comparative results according to the Student-t test with 95% confidence.

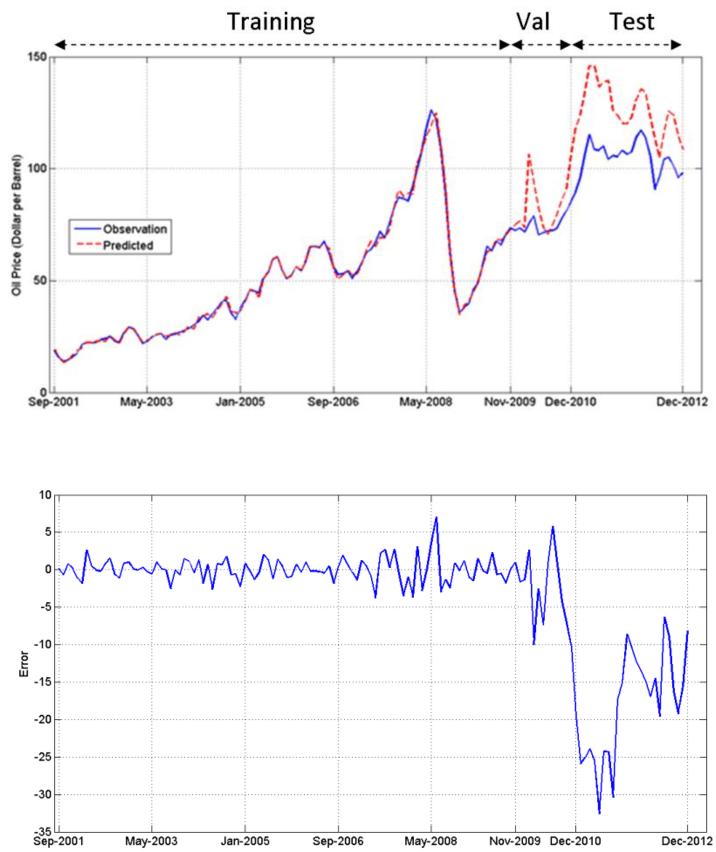

Fig. 2.Predicted oil prices (top) and related error (bottom) from start point inSep.2001 obtained usingANFIS with best input set and proposed radii.

Fig. 2 presents the results of prediction from the start point at Dec-2001. As illustrated in Fig. 2, last 24 months are used for testing the system. The predicted curve illustrated in Figs. 4, is divided into the three segments; the first is the training region that is between months [Sep-2001 Nov-2009]. And the second is the validating region that is between months (Nov-2009 Dec-2010) and the thirds is testing region where the prediction results are validated and it's between [Dec-2010 Dec-2012].

Table 2 Comparative results of price prediction between ANN and ANFIS with proposed variables set

Time series	Model	TrainingSet RMSE	TestSet RMSE	Best Correlation
Oil	**ANFIS**	1.5810±0	22.3565±0	0.98470
	Optimum ANN	7.355527±4.648605	20.3629±14.61734	0.94264

4. Conclusions

ANFIS is an appropriate predictor for OPEC oil price prediction. In contrast to the mathematical model such as ARIMA, ANFIS approach learns pattern-target samples and applies well to adaptive economic problems. The proposed ANFIS with a novel input features set is utilized here to predict the oil prices and considers various economic parameters such as inflation rate, interest rate, OPEC oil production level, silver price, market index and U.S. dollar index.Numerical studies present the following conclusion that ANFIS with the proposed input variables shows higher performance than neural networks in price modeling and can be used in various economic application domains.

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