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Intelligent Decision Support Systems for Oil Price Forecasting

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Abstract. This research studies the application of hybrid algorithms for predicting the prices of crude oil. Brent crude oil price data and hybrid intelligent algorithm (time delay neural network, probabilistic neural network, and fuzzy logic) were used to build intelligent decision support systems for predicting crude oil prices. The proposed model was able to predict future crude oil prices from August 2013 to July 2014. Future prices can guide decision makers in economic planning and taking effective measures to tackle the negative impact of crude oil price volatility. Energy demand and supply projection can effectively be tackled with accurate forecasts of crude oil prices, which in turn can create stability in the oil market. The future crude oil prices predict by the intelligent decision support systems can be used by both government and international organizations related to crude oil such as organization of petroleum exporting countries (OPEC) for policy formulation in the next one year.

Keywords: Decision support system, Time delay neural network, Probabilistic neural network, Fuzzy logic, Crude oil prices

1. Introduction

Regular short-term movements in crude oil prices are caused by normal market forces, including, but not restricted to, US refinery capacities, an OPEC crude oil production ceiling, and global demand and supply, whereas the volatility of the oil market is prompted by uncertain events consisting of, but not narrowed to, wars, revolutions, earthquakes, oil worker strikes, and hostage takings (Alizadeh and Mafinezhad, 2010). Different aspects of society and the world economy require crude oil for its survival. Both academics and industries across the globe perceive the prediction of crude oil prices as a source of concern. From the perspective of industries, crude oil price prediction is an integral part of the process of making decisions in terms of valuation, exploration, development, and production. Short and long-term decision-making processes, national policies, and governments reserved, are affected by crude oil price prediction (Yang *et al*., 2002). Crude oil price volatility contributes to declination in global economic growth and higher interest rates in advanced economies (Yun and Jae, 2010). An overwhelming majority of the literature concentrated on predicting crude oil prices with only regular factors affecting crude oil price movements (e.g., Ghaffari and Zare, 2009; Jammazi and Aloui, 2012).

However, very few consider both regular factors and uncertain events. For example, Yu *et al*. (2005) used rules-based expert systems to forecast the price volatility of crude oil based on significant factors that affect crude oil erraticism. Conversely, rules-based expert systems cannot handle new cases automatically, and they lack the capability to identify nonlinear association, whereas neural networks

(NNs) can automatically handle new patterns by updating its learning, and any nonlinear relationship can be modeled Niculescu (2003). Documentary evidence in a study by Bahrammirzaee (2010) shows that hybrid intelligent systems are superior to a single intelligent technique because they capitalize on their strengths and eliminate their limitations.

Fuzzy logic is good for knowledge representation, whereas an NN is bad. On the other hand, the ability of an NN in terms of adaptability is good, whereas it is bad in fuzzy logic (Dideková and Kajan, 2013). Also, fuzzy logic can model the uncertain behavior of the crude oil market (Gholamian, 2005).

In this paper, we hybridized the two computational algorithms to eliminate their weaknesses and utilized their strengths in our proposal. Backpropagation is the most popular NN algorithm in forecasting, classification, and pattern recognition; however, the network can only map static patterns that are independent of time (Kim *et al*., 2005), which makes the network unsuitable for the time series data of our study. Thus, time delay NN (TDNN), which effectively circumvents the time limitation of back-propagation (Kim *et al*., 2005), is proposed for the study. Probabilistic NN (PNN) is also chosen for the purpose of this research because the network has the capability to interpret the network structure in the form of a probability density function, and its performance is better than other NN classifiers (Specht, 1995).

Other components of the paper are as follows: section 2 introduces the theories of computational algorithms proposed in our study, section 3 provides a detailed description of the algorithms applications, and section 4 presents the results and discussion before the concluding remarks in section 5.

2. Theories of the computational algorithms

2.1 Time Delay Neural Network

According to Kim *et al*., (2005), TDNN activation functions are managed by the storage of delays and error signals for every neuron and all time delays (TD). This activity makes TDNN architecture more complex than the back-propagation network. The TDNN learns time and relationship functions which correlate input vectors with the network-predicted values. TDNN is a category of feed-forward neural network in which its hidden and output neurons are simulated across time. Let the generic time instance delay of TDNN be t; outputs of preceding neurons at different time steps be $t-1, t-2, \ldots, t-n$; and all be summed and connected with appropriate weights. The training of TDNN is through temporary enlargement of TD over all the input data. Assuming an NN with levels L, consisting of N_l units at every level l, the delay input vector y for units i to l at time t can be defined as $y_i(t) = [y_i(t), y_i(t-l), \ldots, y_i(t-T_l)]^T, i = 1, \ldots N_l$. Each input y_i in the preceding layer is computed and transferred as output to neuron j, y_j, of l can be defined as $w_{ji} = [w_{ji}(0), w_{ji}(1), \ldots, w_{ji}(T_1)]^T$, $j = 1, \ldots, N_{l+1}$. Contribution (C_j) from neuron i to neuron j is expressed as $C_{ji}(t) = w_{ji}^T y_i(t)$. Output of the neuron with a transfer function (f) is expressed as $y_j(t) = f(C_j(t))$, and the prompt error (e_i) can be defined as $e_i(t) = d_i(t) - y_i(t)$, where $d_i(t)$ is the target vector *ith* and $d_i(t)$ is given to the NN. The prompt square error is defined as $e^2{}_i(t) = \sum_{i=0}^{N_l} [d_i(t) - y_i(t)]^2$, and the total square error is expressed as $e^2 = \sum_{t=0}^{T} e^2(t)$. Since training TDNN is supervised at every t and the TDNN output depends on TD inputs $t, t-1, \ldots, t-T_1$, $d(t)$ is adaptively synchronous with the input at each t.

2.2. Probabilistic Neural Network

The PNN was first pioneered by Specht (1990). PNN is also a category of feed-forward neural network which consists of three layers of neurons—namely, input, a hidden layer containing radial basis, and lastly, competitive. The first layer feed inputs data to the hidden layer neurons. Distances among inputs to the training vectors are computed by radial basis function. The computed results indicate the closeness of input to a training input. The last layer of the PNN summed the contributions produced by every class of input to produce the PNN probabilities output. At the last layer, the competitive transfer function classifies the inputs due to its optimum probability of classification accuracy (Mantzaris *et al*., 2011). In contrast to other types of NN, PNNs are only applicable in solving classification problems, and the majority of their training techniques are easy to use. Assuming PNN accepts a vector (x) as input, $x = (x_1, ..., x_n)$ is applied to neurons in input layer $x_i (1 \le i \le n)$ and is then fed to hidden layer neurons. At the layer of hidden neurons, M_k Gaussians $\lambda(\mu^k, \sum_j^k)$ are computed for every class $k(1 \ge i \le c)$:

$$p_j^k(x) = \frac{1}{(2\pi)^{\frac{n}{2}} \left| \sum_j^k \right|^{-\frac{1}{2}}} \ell^{[-\frac{1}{2}(x-\mu_j^k)^T (\sum_j^k (x-\mu_j^k)}},$$

where μ_j^k = mean distribution, $\sum_j^k$ = covariance matrix, and M_k = multivariate distributions.

The class probability function $O_k(x) = \sum_{j=1}^{m_k} \pi_j^k p_j^k(x)$ is computed, where π_j^k = within class proportion. The π_j^k is nonnegative and shows $\sum_{j=1}^{m_k} x_j^k = 1, k = 1,..,c$. The third layer of the network computes a decision expressed as $\rho_k(x) = \sum_{l=1}^{c} v_l^k \alpha_l O_l(x)$, where cost function = v_l^k, class = l, and pattern = x. $l = \arg\min\{ \sum_{l=1}^{c} v_l^k \alpha_l O_l(x) \}$. The PNN decision of class l that has minimum risk ρ_l would then be chosen (Berthold and Diamond, 1998).

2.3 Fuzzy Logic

Fuzzy set theory Zadeh (1965) is develop to handle vagueness and subjectivity of linguistic variables which are produce by decision makers in assessing qualitative factors. Linguistic variables can be expressed using different types of Membership Functions (MFs). Selection of MF is based on application and expressed linguistic variables. Triangular Membership Function (TMF) is suitable when there is various input MFs to be aggregated (Chen, 2000). Here are some of the major definitions of fuzzy sets (Zimmermann, 2001):

Definition 1. A fuzzy set $\widetilde{A}$ in a universe of discourse X is characterized by a MF $\mu_{\widetilde{A}}(x)$ that is associated with every element x in X a real number in the interval [0, 1]. The function value $\mu_{\widetilde{A}}(x)$ is termed the grade of membership of x in $\widetilde{A}$.

Definition 2. A Triangular Fuzzy Number (TFN) $\tilde{a}$ defines through a trio (l, m, u) shown in Figure 1. The MF $\mu_{\tilde{a}}(x)$ is defined as follows:

$$\mu_{\tilde{a}}(x) = \begin{cases} (x-l)/(m-l), & l \le x \le m \\ (u-x)/(u-m), & m \le x \le u \\ 0, & \text{Otherwise} \end{cases} \quad (1)$$

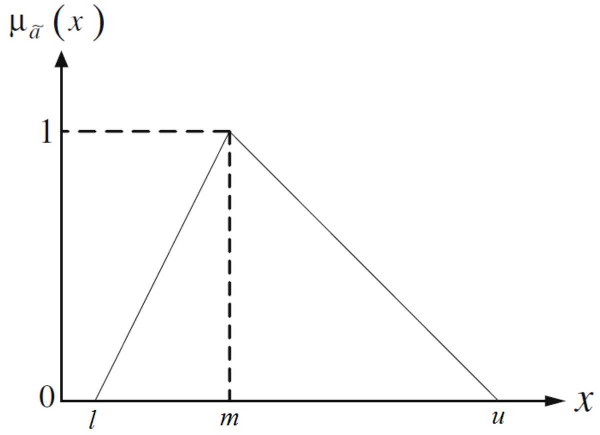

Figure 1: Triangular fuzzy number ã

Let $\tilde{a}_1$ and $\tilde{a}_2$ be two TFNs defined through the trio (l1, m1, u1) and (l2, m2, u2) respectively, then the related operating rules are as follows:

$$\tilde{a}_1 + \tilde{a}_2 = (l_1, m_1, u_1) + (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2), \quad (2)$$

$$\tilde{a}_1 - \tilde{a}_2 = (l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - l_2, m_1 - m_2, u_1 - u_2), \quad (3)$$

$$\tilde{a}_1 \times \tilde{a}_2 = (l_1, m_1, u_1) \times (l_2, m_2, u_2) = (l_1.l_2, m_1.m_2, u_1.u_2), \quad (4)$$

$$\tilde{a}_1 / \tilde{a}_2 = (l_1, m_1, u_1) / (l_2, m_2, u_2) = (l_1/u_2, m_1/m_2, u_1/l_2), \quad (5)$$

$$k * \tilde{a} = (k.l, k.m, k.u). \quad (6)$$

Definition 3. Linguistic variables are variables with linguistic term values. The concept of a linguistic variable is very useful in dealing with situations which are too complex or too ill-defined to be reasonably described in conventional quantitative expressions (Chan *et al*., 2000; Chen, 2000; Zadeh, 1965). Fuzzy expert system is based on fuzzy MFs and fuzzy “if-then” rules. In fuzzy expert system the appropriate MF should be determined based on the aspects involved in the considered factors. The rules of expert system are based on expert opinions, and they should emulate the expert’ evaluations as much as possible.

3. Methods

3.1 Data

Brent crude oil price data sets were collected on a monthly basis for the design, validation, and testing in this research. The data sets were obtained from the US Department of Energy for the period January 1987 to December 2011. The data were partitioned into training, validation, and testing with ratios of 70%, 15%, and 15%, respectively, according to convention in (Beale *et al*., 2013). The experimental data of our study were not normalized because the use of the linear activation function in the output layer of an NN invalidates data normalization and thus renders the data preparation exercise meaningless (Peter *et al*., 2001). An NN automatically adjusts its weights adaptively; therefore, data normalization is not necessary (Zhang *et al*., 1998).

3.2 Application

The proposed framework for the study is shown in Figure 2 adapted from Shouyang *et al*. (2005), when applied to crude oil price prediction. The main stages involve the collection of Brent crude oil price time series data and qualitative data, fuzzy rule creation based on MFs, TDNN prediction, PNN classification, and ensemble prediction. The process begins by extracting data and fed into the systems, the data are tested for confirmation to determine whether they are time series or qualitative or both. After scrutinizing the data and finding that these relevant and important qualitative factors are not in the data, the TDNN module used the time series historical data to execute and predict crude oil prices without considering the fuzzy rules and PNN module. In modeling TDNN architectural configurations, in addition to the factors required in designing an NN model, such as transfer function, learning algorithm, number of hidden layer neurons, etc., effectiveness of an NN model depends on the optimal selection of these parameters to be used in designing the NN architecture. TDNN requires the estimation of TDs for use in each neuron of the architecture as well as other parameters listed earlier. The common technique used for realizing the optimal value of TDs is preliminary experimentation with samples of the entire data. In this study, we use preliminary experimentation since the ideal framework for choosing these optimal parameters required in the design of NNs is lacking, although mutual information can also be used for determining TDs but is cumbersome and requires high computational complexity (Kim *et al*. 2005). After our trial-and-error experimentation, we obtain the following parameters: ten (10) hidden layer neurons, sigmoid activation function at the hidden layer, linear activation function at the output layer neuron, seven (7) input neurons and one (1) output neuron, Levenberg-Marquardt learning algorithm, time is realized is one (1) and two (2) number of TDs in each of the neurons in the TDNN model. The definition of the problem can be expressed as $y(t) = f(x(t-1),...,x(t-d), y(t-1),..., y(t-1)$, where d is the number of delays, t is time, and $y(t)$ represents the future value of the crude oil time series data. If the systems ascertain that significant factors that impact on crude oil prices exist in the data based on the rules defined in the systems, the systems convert these factors to fuzzy rules according to MFs.

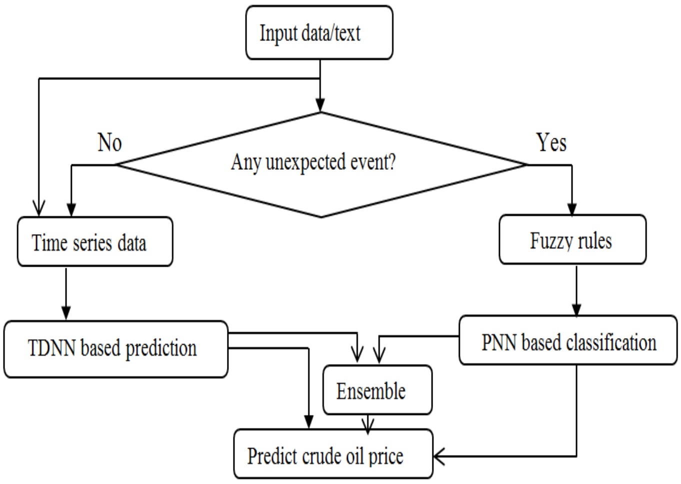

Figure 2: The propose intelligent decision support systems (IDSS) framework

The fuzzy rules in Table 1 were created for our proposed framework based on factors that significantly impact on crude oil price volatility, which includes demand/supply and unexpected events. Examples of such factors are total world demand, non-OPEC production capacity, revolutions in oil-producing countries, hostage crises, etc. A full list and details of these factors can be found in a study by (Yu *et al*., 2005). The considered factors include both qualitative and quantitative factors. Qualitative factors were measured based on experts' judgments. The experts express their judgment using linguistic variables along with uncertainties. Therefore, we design fuzzy "if-then" rules in an expert system to overcome these uncertainties and use them in our model. We design 110 rules (see Table 1) to cover all possible situations related to oil price movements.

Table 1: Fuzzy rules

No. Rule	**Qualitative Factors**										**Oil price movement**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
1	H[1]	H	M	H	H	L	H	H	H	H	AH
2	M	H	L	L	M	L	L	L	H	M	ML

[1] AH (Absolutely High), VH (Very High), MH (Moderate High), FH (Fairly High), H(High), M(Moderate), L(Low),), FL (Fairly Low),), ML (Moderate Low), VL (Very Low), AL (Absolutely Low).

3	L	L	M	M	L	L	M	M	M	M	FL
4	H	H	M	M	M	M	M	M	M	M	H
5	M	L	H	H	H	H	M	M	M	M	FH
6	L	M	H	L	H	H	H	M	H	H	MH
7	H	H	H	H	M	H	M	H	H	H	VH
8	M	L	L	L	L	M	L	L	L	L	VL
9	M	M	M	M	M	M	M	M	M	M	M
10	H	H	H	H	H	H	H	H	H	H	AH
11	L	L	L	L	L	L	L	L	L	L	AL
12	L	H	L	H	H	L	H	L	L	H	M
13	L	H	H	L	H	L	M	M	M	M	M
14	H	H	L	L	M	H	H	H	M	H	H
15	H	L	M	H	H	H	H	H	M	H	H
16	L	M	M	L	L	L	L	L	M	L	L
17	L	L	L	M	H	H	M	M	M	L	L
18	H	H	M	M	L	L	L	L	L	M	FL
19	L	L	L	H	L	L	M	M	L	L	VL
20	H	H	H	H	H	L	M	L	H	H	VH

The fuzzy rules serve as inputs to PNN for modeling and classification of the crude oil price movements. The PNN classifier used in this research consisted of ten (10) input nodes corresponding to the first ten (10) columns of the fuzzy rules. One hidden layer contains eleven (11) neurons, and radial basis transfer function is used. The output layer contains eleven (11) neurons corresponding to the possible movements of prices as indicated in table 1, and a competitive transfer function was applied to classify the movements of crude oil prices based on the PNN probabilities output produced by each fuzzy rule. The parameters used in the classifier were realized through the preliminary experimentations.

In the situation where both qualitative factors that affect crude oil price volatility and time series data of crude oil prices are supplied to the systems, TDNN executes the crude oil time series to predict the prices, and the PNN classifier is also executed. Predicted results produced by both models are assembled to predict an ensemble of predicted crude oil prices. An adaptive linear neural network (ALNN) containing one layer and containing pure linear transfer function with the Widrow-Hoff learning algorithm (Hagan et al., 1996, as cited in (Yu *et al*., 2008) is used for reassembling the results produced by the TDNN model and PNN classifier to yield ensemble predicted prices.

4. Results and discussion

The proposed framework description presented in Figure 2 can be used to predict crude oil prices by considering factors affecting crude oil price volatility as much as possible. Experiments are conducted based on the proposal, and results are presented in this section.

4.1 Time Delay Neural Network Module

The prediction of crude oil prices in the training, validation, and testing phases is shown in Figure 3. It can be observed that the performance of the systems is good. The simulation performance of the TDNN model was evaluated on mean square error (MSE) and regression (R). The value of MSE is 0.165893. The fit of the TDNN output over response time is shown in Figure 3. The MSE of training and validation are 0.1815787 and 0.4030101, respectively. It suggests that the model performs relatively well. The training stopped as cross-validation was not improving and MSE started increasing.

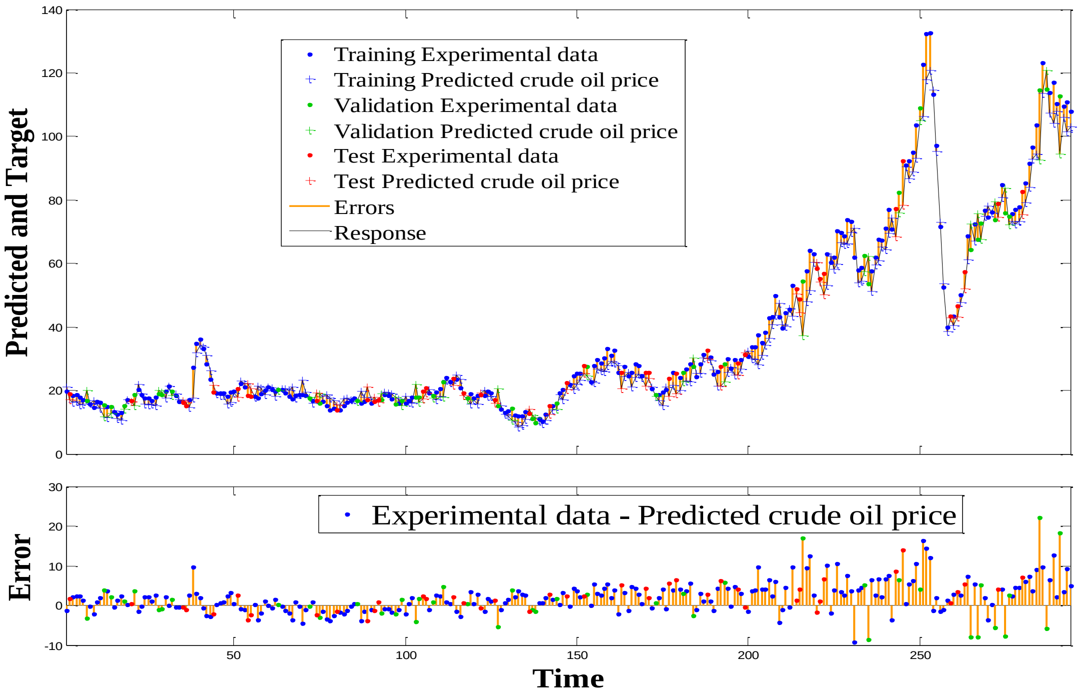

Figure 3: Response time of the TDNN model over prediction error

The results of the linear relationship between the predicted and actual crude oil prices for the test data set are shown in Figure 4. The relationship shows a good fit, with an *R* value more than 0.9. It also indicated that there are some value points that exhibited a poor fit with the corresponding experimental data. For instance, there is a predicted value in the same Figure 4 that has a value of 74, and the corresponding experimental data has 85.

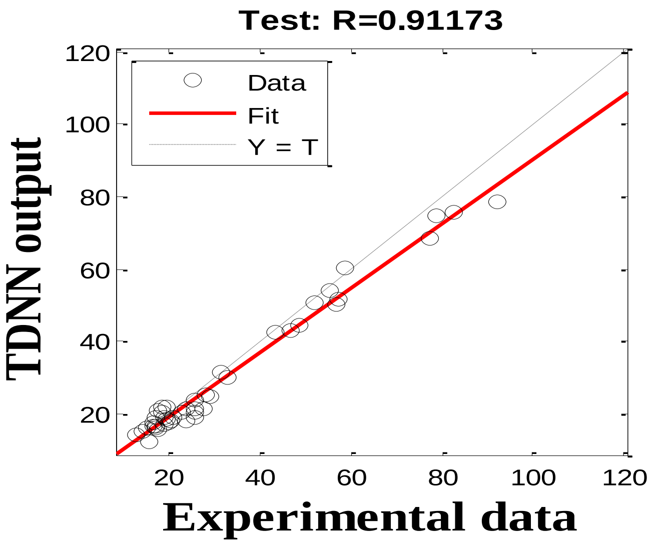

Figure 4: Regression plot of test data set

4.2 Probabilistic Neural Network Classifier Module

The PNN classifier was constructed, and its classification accuracy was tested. The three-level architectural configurations of the classifier were found as stated in section 3. The optimal value of the radial basis function, which is the width of Gaussian, was found to be 0.3. The evaluation criterion for our classifier is the MSE. Table 2 displays the confusion matrix generated by the proposed PNN classifier at a threshold of 0.5. Results generated by the PNN classifier with satisfactory performance are reported in Table 2. The crude oil price movements were detected and classified as L, AL, M, VL, VH, MH, FH, H, FL, ML, and AH, with MSEs of 0.4, 0.33997307, 0.00068039, 0.19406102, 0.09298502, 1.5668E-05, 0.04627412, 0.01020823, 0.16888191, 0.010194, and 0.08116714, respectively. These results suggested that the best performance occurred in the M crude oil price movement with the minimum value of MSE signifying very good detection and classification of price movement patterns.

Table 2: Confusion matrix

Output / Desired	L	AL	M	VL	VH	MH	FH	H	FL	ML	AH
L	0	0	0	0	0	0	0	0	0	0	0
AL	1	0	0	1	0	0	0	0	1	0	0
M	0	0	0	0	0	0	0	0	0	0	0
VL	0	0	0	0	0	0	0	0	0	0	0
VH	0	0	0	0	0	0	0	0	0	0	0
MH	0	0	0	0	0	0	0	0	0	0	0
FH	1	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	0	0	0	0	0	0
FL	0	0	0	0	0	0	0	0	0	0	0
ML	0	0	0	0	0	0	0	0	0	0	0
AH	0	0	0	0	1	0	0	0	0	0	0

Due to the probability of misclassification of a crude oil price movement, the decision makers need to be aware that the classifier only provides knowledge of the level of direction in which the oil market moves. This does not change the fact that any change in oil market patterns calls for immediate decisions to be made. Its use lies in supporting any decision made in regard to the movement of crude oil prices.

4.3 Ensemble Predicted Crude Oil Price

Three computational algorithms—namely, fuzzy logic, TDNN, and PNN were hybridized as mentioned earlier to create IDSS. TDNN and PNN predicted the oil prices as a separate constituent, and the predicted results are recombined by ALNN because the ensemble results are superior to an individual algorithms result (see Table 3). Figure 5 shows the ensemble crude oil prices predicted by the IDSS with a very low MSE as reported in Table 3. It can be observed that the performance of the IDSS model is very good as both plots of predicted and actual prices are very much closer in terms of the patterns detected by the intelligent model.

Table 3: Comparisons between the performances of the IDSS and constituent algorithms

Model	**Performance (MSE)**
TDNN predictor	0.165893
PNN classifier	0.000680
IDSS	0.00002521

Results presented in Table 3 suggest that a hybrid of the intelligent systems (IDSS) performs better than each individual algorithm. Although each algorithm can complement each other as already described earlier. The superiority in the performance of the hybrid system might probably be caused by the elimination of shortcomings associated with each of the algorithm due to their hybridization.

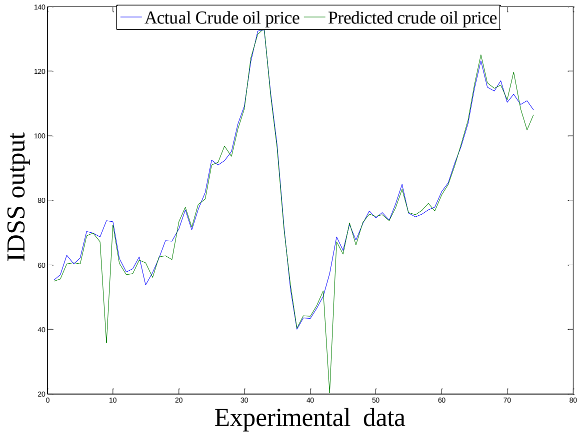

Figure 5: Ensemble prediction of crude oil prices by the proposed IDSS

Correlation between the two set of data presented in Figure 5 was investigated. The value of the Pearson's correlation coefficient (r) at 0.01 significant level is r = 0.985 and was obtained from the relationship between Actual crude oil price and Predicted price, which shows that there is significant strong positive correlation relationship. This relationship indicates that increases or decreases of the actual crude oil price also apply to the predicted price. The modeling procedure in our research covers several procedures as already described in preceding sections. These procedures suggest that the proposed model will achieve its desired purpose. The performance exhibited by the model gives the first insight into the representation expected in real-life systems. The results generated by IDSS confirm the model has generated the desired results. Since the results produced by the proposed systems are correlated with that of actual data, the proper verification of the implementation assumption is achieved, and it constitutes a true representation of a real-life system (Taher, 2013). Therefore, the proposed IDSS is deployed to predict monthly crude oil prices for the next one year ahead.

4.4 Predicted Future Brent Crude Oil Prices up to July 2014

Figure 6 shows Brent crude oil prices predicted by our IDSS developed in this research. The prices are predicted for the next one (1) year into the future up to July 2014. A close observation of the plot indicated that the prices will continue to fluctuate, moving up and down as seen in the past (refer to Figure 5), signifying uncertain behavior, although this kind of behavior is expected in the crude oil market. The future prices indicate that our proposed model was able to generalize well and detect patterns through which the oil market might follow in the next one year to come. Several countries' budgets, such as those of Saudi Arabia, Kuwait, Venezuela, Nigeria, Iran, Iraq, and Russia, heavily depend on expected revenue accrued from the sales of crude oil. Accurate prediction of the future prices is very critical to their national planning, policymaking, and development. Even non-oil-producing countries require knowledge of future prices of crude oil for strategic and industrial usage, which might drive their economic development, which in turn might improve economic standards. Suggestions from the predicted prices show that our model has the potential to be deployed by these countries as a complementary tool for supporting their decision-making processes. Inter- governmental organizations such as organization of petroleum exporting countries and organization for economic co – operation and development can use our projected oil prices for making decisions on oil production, consumption, supply, refinery stocks, etc., or for modifying their existing policies for the next one year.

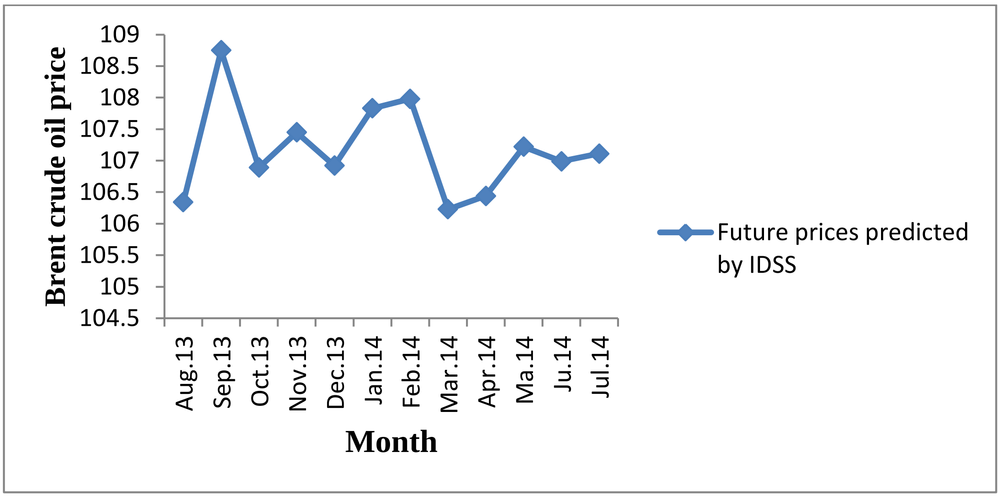

Figure 6: Monthly predicted Brent crude oil prices from August 2013–July 2014

The negative impacts of crude oil price volatility can be tackled with accurate forecasting of crude oil prices, which in turn might reduce the suffering of price volatility inflicts on communities.

5. Conclusions

The IDSS presented in this study are a hybrid of fuzzy logic, TDNN, and PNN. The systems might guide decision makers in economic planning and taking effective measures to tackle the negative effects of crude oil price volatility. The proposed systems can be used to set future prices of crude oil. Energy demand and supply projections can be effectively tackled with accurate forecasting of crude oil prices (Kaboudan, 2001), which can create stability in the oil market (Aladwani and Iledare, 2013).The IDSS propose in this paper was able to predict monthly future crude oil prices starting from August 2013 to July 2014. The predicted future crude oil prices presented in this research can be used by both government and international organizations related to crude oil for policy formulation for the next one year.

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