Hybrid Functional Networks for PVT Characterisation

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***Abstract*—Predicting pressure volume temperature properties of black oil is one of the key processes required in a successful oil exploration. As crude oils from different regions have different properties, some researchers have used API gravity, which is used to classify crude oils, to develop different empirical correlations for different classes of black oils. However, this manual grouping may not necessarily result in correlations that appropriately capture the uncertainties in the black oils. This paper proposes intelligent clustering to group black oils before passing the clusters as inputs to the functional networks for prediction. This hybrid process gives better performance than the empirical correlations, standalone functional networks and neural network predictions.**

***Keywords*—PVT; API gravity; clustering; functional networks; neural network**

I. Introduction

The API gravity is one of the important pressure volume temperature (PVT) properties of crude oils. Crude oil is classified based on this property to determine its heaviness which consequently determines its marketability. Table I shows a typical oil classification based on API gravity [1], [2]. Knowledge of the API gravity and other PVT properties such as bubblepoint pressure (P_b), oil formation volume factor (B_0) and oil viscosity are important for determining future production or oil reserves from petroleum wells.

Some of the PVT properties, e.g. API gravity, can easily be measured or determined onsite while others, e.g. P_b and B_0, are ideally determined through laboratory experimentation. However, this laboratory analysis, which requires special expertise, is expensive and time consuming. Hence, there is a need for a less rigorous, cheaper and quicker solution.

For a long period of time the petroleum industry has used equations of states (EOS) for determining these PVT properties. However, the EOS are considered computationally complex and require extensive detailed compositions of reservoir fluids. Consequently, many empirical correlations have been developed to meet the industrial demands for less complex, quicker, cheaper and acceptable solutions.

TABLE I. Crude Oil Classification based on API

Classification	API Range
Light	API $>$ 31.1
Medium	22.3 $\leq$ API $\leq$ 31.1
Heavy	API $<$ 22.3
Extra Heavy	API $<$ 10.0

Empirical correlations for predicting PVT properties are generally developed by performing linear or non-linear regression analysis using easily acquired crude oil properties as the inputs. In order to improve the performance of the correlations, some researchers have used API gravity to group crude oils into two or more groups and determine correlations for each group [3].

For more reliable and improved prediction performance of these PVT properties, other researchers have implemented machine learning [ML] algorithms to predict different PVT properties [4]–[7]. However, none of the previous works found in the literature which have applied ML techniques in this field, have taken diversity of API or other input properties into consideration. For instance, if the data that are used to train an ML algorithm have more light crude oils than heavy oils, then the model is confined to the constraints of the light oils. This type of data is called imbalanced data set which is well known in the classification problem [8].

This paper proposes a hybrid solution of K-Means clustering and functional networks (FN) for predicting crude oil PVT properties. K-means clustering is used to generate clusters of the input dataset before using functional networks to perform the prediction of the actual target variables, P_b and the oil formation volume factor at bubblepoint pressure (B_{0b}). The performances of the hybrid solution (K-Means+FN) is compared with the standalone FN, feed forward neural network (FFNN) and selected empirical correlations which are either commonly used in the petroleum industry or recently developed.

The rest of the paper is organised as follows. Section II discusses the empirical correlations and ML methods that have been used to predict different PVT properties. A brief explanation of K-Means clustering and functional networks in comparison with neural networks is given in section III. This is followed by the proposed hybrid solution in section IV. Results and discussion of the performances of the hybrid model and other compared models are done in section V with

a brief analysis of sensitivity of FN learning parameters. The conclusion is given in section VI.

II. Research Contribution

In this paper, a hybrid of K-Means cluster and FN has been developed to estimate PVT properties. This paves way for intelligent grouping or clustering of crude oils. Also unlike the existing practice where only the API gravity of crude oils is used for grouping them, all the independent variables are used for grouping the crude oils.

III. Methods for Predicting PVT Properties

Aside the EOS, there are two main categories of methods for predicting PVT properties in the literature: empirical correlations and ML techniques.

A. Empirical Correlations for Predicting PVT Properties

Many correlations have been developed for the estimation of P_b and B_{ob}. Usually, the procedure involves linear and/or non-linear regressions on the available data sets.

Standing developed graphical correlations for both P_b and B_{ob} based on 105 sets of experimental data [9]. These graphical correlations were later expressed by equations [10]. The input variables that Standing used for the P_b correlation are: gas solubility (R_s), gas gravity (γ_g), oil API gravity (γ_{API}) and reservoir temperature (T). For the B_{ob} correlation, the correlating parameters were: R_s, γ_g, oil gravity (γ_o) and T. On this basis, many other correlations have been developed for both P_b and $B_o b$ [2], [11]–[16].

For P_b, Standings functional form is:

$$P_b = f(R_s, \gamma_{API}, \gamma_g, T). \tag{1}$$

For the B_{ob} correlation, the most common functional form is

$$B_{ob} = f(R_s, \gamma_{API}, \gamma_g, T). \tag{2}$$

B. Machine Learning Techniques for Predicting PVT Properties

The quest for better PVT prediction.models to improve the current performances of the empirical correlations has driven applications of different ML techniques in PVT characterisation. The most commonly used ML technique for PVT prediction is artificial neural network (ANN) and its variants [17]. While many of the authors have reported good performance from the developed ANN models, others have pointed out that ANN may not necessarily perform better than the empirical correlations [11]. It should be noted that the performance of any ML model depends on careful selection of its learning parameters.

The black box representation of ANN has made it unattractive for adoption in industrial PVT application. Sequel to this, some representative ML and evolutionary techniques have been used such as support vector machine (SVM), genetic algorithm (GA), adaptive neuro fuzzy system (ANFIS), functional networks (FN) and so on [5], [7], [18].

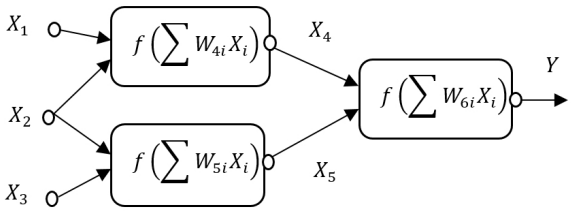

Fig. 1. A Standard Neural Network

Generally, an ML solution usually involves minimization of the error in the learning algorithm. It is notable that many of the machine learning algorithms work by performing a local search that may become stuck in a local minima which causes the model to perform poorly when presented with new data [19]. An ML model could be stuck in local minima as a result of inefficient learning parameters or imbalanced data sets. However, this problem has not been adequately addressed in prediction of PVT properties with ML techniques though some efforts have been made in empirical correlation development with some possible accuracy improvement [3]. However, this involves manual grouping of crude oils and generating different correlations for the groups. This paper proposes intelligent clustering of data before applying an ML technique to the generated clusters.

IV. Hybrid Machine Learning System

Hybrid ML system is normally developed so that the consisting sub-systems complement each other. The aim of a hybrid system is to fill the gap that a single method cannot necessarily fill. This paper implements a hybrid of K-means clustering and FN.

A. K-means Clustering

K-means is a widely used data mining technique. It puts a number of input observations into a number of clusters which must have been defined a priori. The goal of clustering is to allow natural grouping of data [20]. The implementation, pros and cons of the K-Means algorithm have been well discussed in the literature [20].

B. Implementation of Functional Networks

FN were introduced as a powerful alternative to neural networks [21], [22]. Unlike neural networks, functional networks have the advantage that they use domain knowledge in addition to data knowledge. The network initial topology can be derived based on the modelling of the properties of the real world. Once this topology is available, functional equations allow one to obtain a much simpler equivalent topology.

Simplified general topologies for ANN and FN are shown in Fig. 1 and 2. In these figures, X_1, X_2 and X_3 are the inputs into the network. X_4 and X_5 are the outputs of the hidden layer. W_{mn} (m = 4, 5, 6; n = 1, 2, 3, 4, 5) are the weights while Y is the output in both cases.

There are some quite significant differences between ANN and FN. Notably, the functions in FN are truly learned during the structural learning unlike the ANN where neuron functions

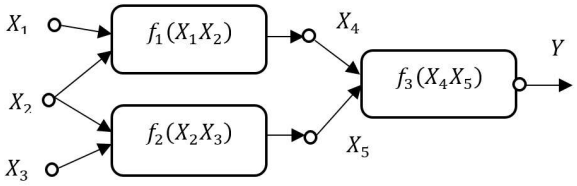

Fig. 2. A Standard Functional Network

are assumed to be fixed and known and only the weights are learned. The implemented FN is shortly described below.

Given a data set $\{x_{ij}|y_i; i = 1, 2, ..., n; j = 1, 2, 3, 4\}$ where x_{ij} are the predictors and y_i is the output. Mathematically, the relationship can be given by

$$Y = f(X_1, X_2, X_3, X_4) \tag{3}$$

Note that j refers to the number of inputs which is 4 here. The general form of a functional network that learns from the data can be given as follows [22]:

$$y_i = sum_{j=1}^{p} \sum_{r=1}^{m} C_r \varphi_r(x_{ij}), i = 1, 2, ..., n \tag{4}$$

where φ_r are the linear independent functions which are used to learn the coefficients C_r. Some possible functions for φ_r are:

1) Polynomial function:

$$\varphi = \{1, x, x^2, ..., x^m\} \tag{5}$$

2) Exponential Function:

$$\varphi = \{1, e^x, e^{-x}, ..., e^{mx}, e^{-mx}\} \tag{6}$$

3) Fourier Function:

$$\varphi = \{1, \sin(x), \cos(x), ..., \sin(mx), \cos(mx)\} \tag{7}$$

4) Logarithm Function:

$$\varphi = \{1, \log(x+2), \log(x+3), ..., \log(x+m)\} \tag{8}$$

The aim is to get which is an estimate of $\hat{Y}$ such that the square of the error ϵ is minimised. That is

$$\min \left\{ \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i \right)^2 \right\}. \tag{9}$$

Hence, the aim is to produce an estimate $\hat{Y}$ that gives minimal error ϵ which can be represented as:

$$\epsilon = \min(Y - \hat{Y}). \tag{10}$$

This final equation can be solved using least square optimization.

1. Input: Get the data X for clustering
2. Data clustering with K-Means to get clusters, D_c, c=1,.., k where k is total number of clusters
3. BEGIN FN Network
3. FOR m=3 to 10
4. Initialise the functional model e.g. $\varphi = \{1, x, x^2, ..., x^m\}$
5. FOR each cluster D_c compute the functional components C
6. END FOR m loop
7. END each cluster loop
8. Combine and evaluate the prediction from the clusters.

Fig. 3. Steps for the hybrid k-means and Functional Networks

C. Proposed Hybrid K-means and Functional Networks

The proposed hybrid implementation is shown in Fig. 3. The clusters serve as inputs to the FN. FN has been specifically chosen for the hybrid modelling as it has been shown to perform very well on both small and large data sets [22]. It is important to note that the clustering takes all the predictors into consideration to generate the clusters unlike the manual grouping based on only API grouping, which is done for some empirical correlations.

All the four functional forms stated above have been tested with degree between 3 and 10 which is sufficient in most cases [22]. The best chosen model is the one that gives both the minimum root mean squared error (RMSE) and average absolute percentage relative error (E_a).

D. Simulations

A total of approximately 1400 data points were available for the simulation. 327 data points were collected from different published papers [12], [23]–[25]. The remaining data are unpublished and they are from different sources such as GeoMark Research and Shell Company. The data comes from diverse crude oils across the globe.

In the hybrid systems, four input clusters have been generated which are passed to the functional networks. All the stated learning functions were tested and the polynomial function of degree five gave the best results for both the hybrid K-Means+FN and the standalone FN. For the ANN model, different activation functions, number of hidden layers and neurons were explored. The best ANN model has been achieved with sigmoid activation, one hidden layer and ten neurons.

V. Results and Discussion

Simulation results of hybrid K-Means+FN for both P_b and B_{ob} are presented and compared with the standalone FN and ANN, popular and recently proposed empirical correlations. Mainly, two statistical error measures, RMSE and E_a are used to compare the prediction capability of the models. Whenever there is a tie between these two parameters, then E_{max} and CC are used respectively for comparison. The lower the error parameters, RMSE, E_a and E_{max}, the better. On the other hand, the higher the CC the better.

A. Comparison of Hybrid K-Means+FN with other Models

For P_b prediction, the proposed hybrid K-Means+FN model gives both minimum RMSE (344.8264) and E_a (11.0829) as shown in Table 2. K-Means+FN hybrid model also has the least E_{max} (81.8879) which implies that it has the least tendency of over-fitting. Likewise, K-Means+FN has the highest CC (0.9652) which is an indication that its predicted output are more correlated with the target than others.

Among all these compared models for P_b prediction, the least performance is in the correlation of [16]. From the results, both ANN and standalone FN also perform better than all the listed empirical correlations.

The results for the B_{ob} prediction are shown in Table 3. Clearly, the hybrid K-Means +FN gives the best performance with the least RMSE (0.0489) and E_a (1.3856). Also the K-Means+FN hybrid has the minimum E_{max} (31.8356) and maximum CC (0.9807). A very significant improvement in performance can be seen in the hybrid system compared to both ANN and standalone FN. However, both ANN and standalone FN trail one of the correlations [15] in performance with respect to both RMSE and E_a.

B. Sensitivity of Functional Network Parameters

In this section, the sensitivity of the FN parameters in the overall performance of the hybrid K-Means+FN models is examined. In the previous section, the best achievable model for the hybrid has been used. Boxplots for the four most important statistical parameters are presented in Figs. 4-7.

It is noted that the performance of the hybrid models, largely influenced by the linear independent function and its degree for the FN, can vary over a wide range. For both P_b and B_{ob}, polynomial function of degree five gave the best performance.

From the box plots in Figs. 4-7, it can be seen that performances of the hybrid K-Means+FN varied significantly for CC, RMSE, E_a and E_{max}. For P_b, CC ranges from 0.9079 to 0.9652, RMSE from 344.8264 to 552.5147, E_a from 11.0829% to 31.2093% and E_{max} from 81.8879% to 2911.8493%. For the B_{ob}, CC ranges from 0.9614 to 0.9807, RMSE from 0.0489 to 0.0689, E_a from 1.3856% to 3.2082% and E_{max} from 31.8356% to 61.7369%.

VI. Conclusion

A hybrid system using K-Means clustering and functional networks has been developed to predict crude oil PVT based on worldwide data which a wide range of different crude oil with diverse thermodynamic properties. The clustering part of the hybrid is inspired by the common API grouping of crude oils.

Functional networks which resemble neural networks in architecture have been used for the actual prediction. The neurons in a functional network are functions defined by the modeller and it does not suffer from the black box indictment, though it is more computational demanding.

For the two PVT properties, P_b and B_ob, that have been modelled in this work, the proposed hybrid system outperforms all the compared empirical correlations, feed forward neural

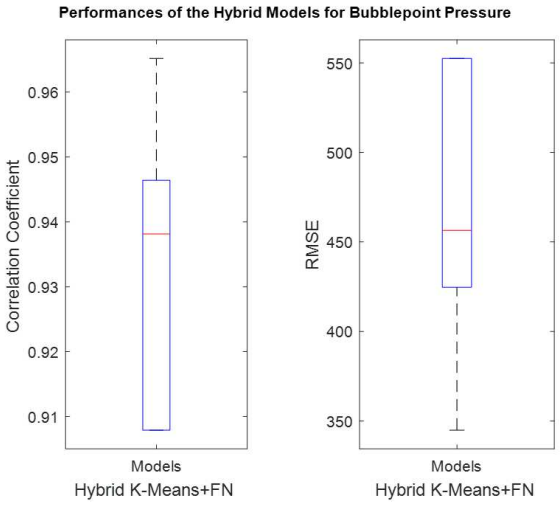

Fig. 4. P_b Boxplot for K-Means+FN and CC/RMSE

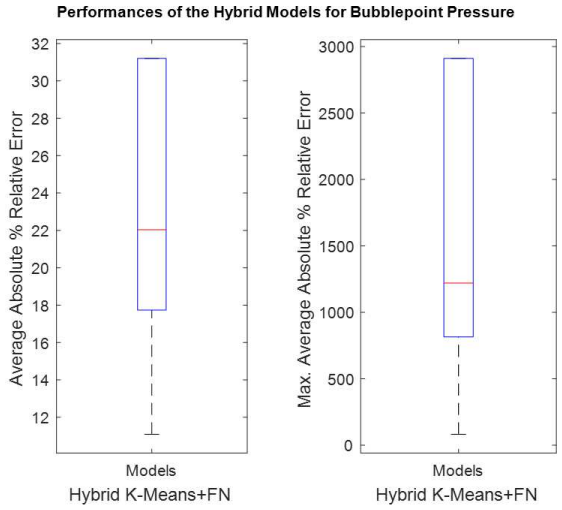

Fig. 5. P_b Boxplot for K-Means+FN and E_a/E_{max}

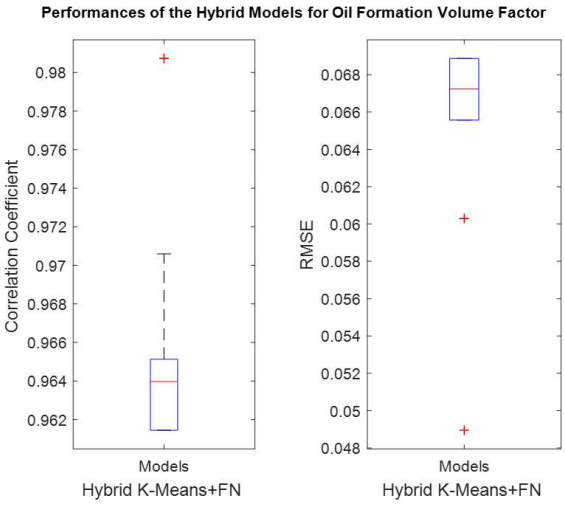

Fig. 6. B_{ob} Boxplot for K-Means+FN and RMSE/E_{max}

TABLE II. MODEL PERFORMANCES FOR BUBBLEPOINT PRESSURE

Correlation Method	CC	$RMSE$	E_r	E_a	E_{min}	E_{max}	SD
Standing [9]	0.9057	616.2760	-3.4038	17.5340	0.0190	548.9583	0.3414
Al-Marhoun [12]	0.9187	812.2788	-12.9768	20.0810	0.0084	388.6760	0.2222
Vazquez and Beggs [13]	0.9091	765.8636	-13.0168	20.6291	0.0212	603.2238	0.4345
Kartoatmodjo and Schmidt [26]	0.8911	882.2240	-11.1193	21.9222	0.0095	602.7154	0.4991
Dokla and Osman [24]	0.8596	678.0152	-5.3107	21.8189	0.0093	511.0192	0.7033
Petrosky and Farshad [15]	0.9347	793.0799	10.7982	39.7123	0.0022	1357.4589	0.0706
Velarde et al. [27]	0.9328	529.5030	-5.2997	14.9442	0.0385	443.4241	0.1801
Al-Shammasi [11]	0.8962	579.3566	-2.2827	18.9615	0.0334	576.1059	0.3534
Dindoruk and Christman [28]	0.9247	540.7703	-6.8919	18.2234	0.0300	467.5842	0.4716
Khamehchi et al. [29]	0.8947	1036.8969	-24.4490	29.5174	0.0142	654.9375	0.8214
Arabloo [30]	0.9104	551.5070	3.4806	16.5968	0.0001	461.4342	0.4964
Jarrahian [16]	0.8597	2004.4451	73.7602	73.8764	25.8628	96.8158	0.1077
ANN	0.9457	410.1738	-1.2703	13.0577	0.0268	117.0041	0.6855
Standalone FN	0.9522	390.5335	-5.6662	14.5618	0.0057	154.4435	0.2733
Cluster + FN (Present work)	0.9652	344.8264	-2.9911	11.0829	0.0056	81.8879	0.1188

TABLE III. MODEL PERFORMANCES FOR OIL FORMATION VOLUME FACTOR AT BUBBLEPOINT PRESSURE

Correlation Method	CC	$RMSE$	E_r	E_a	E_{min}	E_{max}	SD
Standing [9]	0.9574	0.0744	-0.4097	2.2852	0.0007	68.1578	0.1468
Vazquez and Beggs [13]	0.9374	0.0866	0.4498	3.5164	0.0047	63.0057	0.2384
Al-Marhoun [12]	0.9611	0.0716	0.5751	2.2557	0.0007	53.0750	0.0499
Kartoatmodjo and Schmidt [26]	0.9624	0.0679	0.3174	2.1148	0.0025	56.5184	0.0770
Dokla and Osman [24]	0.9594	0.0759	0.5801	3.1316	0.0012	65.1839	0.0101
Al-Marhoun [31]	0.9646	0.0655	0.2331	1.9317	0.0038	57.4667	0.0962
Omar and Todd [23]	0.9434	0.0896	-0.3410	3.1626	0.0119	77.3916	0.2419
Almehaideb [24]	0.9472	0.0834	0.2608	3.8067	0.0055	54.3641	0.0846
Petrosky and Farshad [15]	0.9642	0.0654	-0.0645	1.4851	0.0001	53.0785	0.0902
Al-Shammasi [11]	0.9490	0.0851	-2.6715	3.7926	0.0206	67.3687	0.1473
Dindoruk and Christman [28]	0.9086	0.1128	0.4307	3.3049	0.0012	95.3749	0.0869
Ikiensikimama and Ajienka [32]	0.9629	0.0670	-0.1210	2.1352	0.0013	55.7279	0.0258
Arabloo [30]	0.9636	0.0671	0.4658	2.0435	0.0002	56.2252	0.1346
ANN	0.9507	0.0830	1.4421	2.9658	0.0220	35.6288	0.1405
Standalone FN	0.9699	0.0742	-0.2664	2.0167	0.0095	50.4549	0.2843
Cluster + FN (Present work)	0.9807	0.0489	-0.0714	1.3856	0.0069	31.8356	0.0146

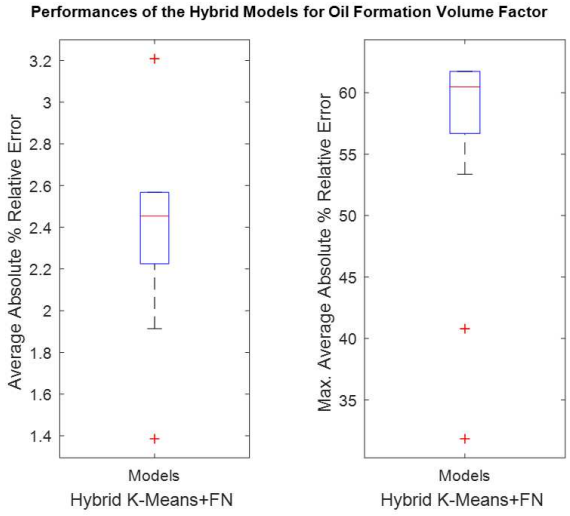

Fig. 7. B_{ob} Boxplot for K-Means+FN and E_a/E_{max}

network and standalone functional networks. The results show that the clustering of the data before prediction by the functional networks has significantly improve the results compared to the standalone functional networks. The attempt to solve the impact of imbalanced data set by pre-processing the data into clusters to prevent domination by most predominant crude oil with similar properties has shown its significance.

It is also clear that the learning parameters of the functional networks must be carefully selected to get a good high performance. It should be noted that different data sets in different problem will probably be modelled by different linear independent functions as expected. Hence, different ones must be explored in each problem to attain the model that appropriately captures the uncertainties in the input data set.

APPENDIX

Statistical Measures for the performance Analysis

A. Average percent relative error

$$E_r = \frac{1}{n}\sum_{i=1}^{n} E_i, \tag{A.1}$$

where,

$$E_i = \left(\frac{X_{exp} - X_{pred}}{X_{exp}} \right)_i \times 100, i = 1, 2, ..., n \qquad \text{(A.2)}$$

B. Average absolute percent relative error

$$E_a = \frac{1}{n} \sum_{i=1}^{n} |E_i \qquad \text{(A.3)}$$

C. Maximum absolute percent relative error

$$E_{max} = \max_i |E_i| \qquad \text{(A.4)}$$

D. Standard Deviation

$$\text{SD} = \sqrt{\frac{1}{(n-1)} \sum_{i=1}^{n} (E_i - E_r)^2}, \qquad \text{(A.5)}$$

where $E_r = \frac{1}{n} \sum_{i=1}^{n} E_i$.

E. Root mean squared

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} E_i} \qquad \text{(A.6)}$$

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