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Research Article

A machine learning approach for estimating the bubblepoint pressure of world crude oils

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ABSTRACT

The pressure at which the first bubble of gas exits the reservoir oil is known as the bubblepoint pressure. This parameter affects multiphase flow in pipes and the overall recovery factor of oil from a reservoir. Therefore, it's crucial to accurately estimate the crude oil bubblepoint pressure. There have been a lot of studies on calculating the bubblepoint pressure from laboratory data, which can be summarized into two main approaches: empirical correlations and machine learning (ML) algorithms. In this study, the authors implement both empirical correlations and ML algorithms with Decision Tree (DT), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Group Method of Data Handling (GMDH). The data was collected from the open literature for world crude oils. The estimation results of the two approaches mentioned above are compared by regression metrics: Mean Squared Error (*MSE*), Root Mean Squared Error (*RMSE*), and Coefficient of Determination (R^2). It was found that the GMDH algorithm has the accurate prediction results with the low *MSE* and *RMSE* (336605.4 and 580.177) and the highest R^2 (0.9228). Trend analysis was carried out to strengthen model selection. The influence of input features on the prediction results indicates that the GMDH algorithm has the most stability. Therefore, the GMDH model is selected for estimating the bubblepoint pressure.

Key words: bubblepoint pressure correlation, decision tree, k-nearest neighbors, artificial neural network, group method of data handling

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INTRODUCTION

In the reservoir's initial condition, oil is a solution that involves gas. The bubblepoint pressure (pb) is defined as the pressure at which the first gas bubbles exit from the oil [1]. Bubblepoint pressure is a key parameter for PVT and fluid properties calculations, production optimization, reservoir characterization, and reservoir simulation. Therefore, it is crucial to accurately calculate the bubblepoint pressure. Typically, bubblepoint pressure is measured by sampling fluid from the reservoir and analyzing the PVT (pressure-volume-temperature). However, this method is expensive and takes a lot of time to implement [2]. For this reason, many mathematical methods have been developed to utilize measured data to quickly and accurately estimate bubblepoint pressure. There are two common approaches for estimating bubblepoint pressure: the first is empirical correlations, and the second is machine learning algorithms. The first approach has many methods with some famous correlations, for instance, Standing [3], Vazquez and Beggs [4], Glaso [5], Al-Marhoun [6], and Petrosky and Farshad [7]. The second approach has undergone formidable development in recent years. In the age of artificial intelligence and machine learning, researchers have more powerful tools to solve petroleum engineering problems. Many studies focus on the application of machine learning for estimating oil bubblepoint pressure. The most common machine learning algorithm and earliest used to estimate p_b is ANN, for example, according to studies by Osman et al. [8], Rasouli et al. [9], Obanijesu and Araromi [10], Alimadadi et al. [11], Al-Marhoun et al. [12], Adeeyo [13], Fath et al. [14], Hassan et al. [15]. Over time, many other vigorous ML algorithms have been implemented for bubblepoint pressure prediction. These algorithms include support vector machines [16–19], genetic algorithms [20,21], or groups of machine learning algorithms [22–24].

In this study, the authors extend predictive methods based on ANN, DT, KNN, and GMDH. Research data collected from the many literature. To identify the most optimal method in this work, we use statistical metrics for the regression problem, including *MSE*, *RMSE*, and R^2.

METHODS

As stated previously, there are two usual methods for estimating the bubblepoint pressure: empirical correlations and machine learning algorithms. Below is a summary of the methods belonging to the two main

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groups above.

Empirical correlations

Standing

In 1947, Stading developed a method for bubblepoint pressure with inputs of solution gas-oil ratio (R_s), gas specific gravity (γ_g), reservoir temperature (T), oil gravity (API)[3].

$$p_b = 18.2\left[\left(\frac{R_s}{\gamma_g}\right)^{0.83}(10)^a - 1.4\right] \quad (1)$$

$$a = 0.00091\,(T-460) - 0.0125\,(API) \quad (2)$$

Vazquez & Beggs

Vazquez and Beggs (1980) proposed a correlation for bubblepoint pressure as follows[4]:

$$p_b = \left[\left(C_1\frac{R_s}{\gamma_g}\right)(10)^a\right]^{c2} \quad (3)$$

$$a = C_3\left(\frac{API}{T}\right) \quad (4)$$

Table 1: C_1, C_2, and C_3 values

Parameter	API ≤ 30	API ≥ 30
C_1	27.624	56.18
C_2	10.914328	0.84246
C_3	-11.172	-10.393

Glaso

In 1980, Glaso developed a method for bubblepoint pressure as below[5]:

$$\begin{aligned}\log(p_b) = 1.7669 + 1.7447\log(A)\\ -0.30218\,[\log(A)]^2\end{aligned} \quad (5)$$

$$A = \left(\frac{R_s}{\gamma_g}\right)^{0.816}\frac{(T-460)^{0.172}}{(API)^{0.989}} \quad (6)$$

Al-Marhoun

Al-Marhoun (1988) presented a simple correlation as follows:

$$p_b = aR_s^b\gamma_g^c\gamma_o^d T^e \quad (7)$$

with a = 5.38088x10^{-3}, b = 0.715082, c = -1.87784, d = 3.1437, and e = 1.32657

Petrosky & Farshad

In 1995, Petrosky and Farshad recommended a correlation as below:

$$p_b = \left[\frac{112/727R_s^{0.577421}}{\gamma_g^{0.8439}(10)^x}\right] - 1391.051 \quad (8)$$

$$\begin{aligned}x = 7.916\left(10^{-4}\right)(API)^{1.5410}\\ -4.561\left(10^{-5}\right)(T-460)^{1.3911}\end{aligned} \quad (9)$$

Machine learning algorithms

Artificial Neural Network (ANN)

An ANN is an algorithm that is based on biological processes and simulates the functions of the nervous system. Typically, an ANN structure has three layers: an input layer, a hidden layer, and an output layer. Each individual node has input data, weights, a bias, and an output. The output values are determined through transfer functions. Some of the most common transfer functions are: the Sigmoid function, the ReLU (Rectified Linear Unit) function, the Leaky ReLU function, the Hyperbolic Tangent function, the Softmax function, and the Heaviside function[25].

The essence of the ANN process is to learn from the data to renew the weights. The updating of the weights is performed continuously through two processes: forward propagation and backpropagation[26].

K-Nearest Neighbors (KNN)

The KNN is a supervised ML algorithm that makes predictions based on the neighbor data points in a feature space. In this algorithm, we choose the K value to represent the number of neighboring points to calculate the distance between the new point and the K neighboring points. Then, identify the K-nearest neighbors with the smallest distances and compute the weighted average of the target values of these neighbors. Finally, assign this average value as the estimated value for the new data[27].

Decision Tree (DT)

The DT is a structure that includes nodes and branches, and class attributes are represented on the internal nodes of the tree. Based on the class attributes, it works by splitting the dataset into subsets. This process is called attribute selection[28].

The Information Gain method is the popular method for attribute selection. This approach calculates the information gain for each attribute and selects the one with the highest gain as the splitting attribute at each node[28].

Group Method of Data Handling (GMDH)

The GMDH was developed by A.G. Ivakhnenko in the 1966 and has found applications in various fields. The basic procedure of GMDH is to construct the high-order polynomial form, which relates input variables to a single output variable. For each feature, build candidate models with different polynomial degrees and evaluate the models' performance using MSE. In the end, perform an iterative solution to find the best overall model with the input features [29].

The Group Method of Data Handling neural network, also known as the GMDH-type neural network, is a GMDH's spectrum that combines the automated model selection of ANN and feature extraction of GMDH [30].

RESULTS AND DISCUSSION

Data

The research data was collected from the open literature on world crude oils [31–37]. It includes 567 data points with descriptive statistics, as shown in Table 2.

Results of estimating the bubblepoint pressure (BPP) of world crude oils

Empirical correlations

a. Standing correlation

Using equations (1) and (2), we have the predicted results versus measured results of BPP, shown in Figure 1.

b. Vazquez & Beggs correlation

Using equations (3) and (4), we have the comparison results shown in Figure 2.

c. Glaso correlation

Using equations (5) and (6), we have the predicted results versus measured results of BPP, shown in Figure 3.

d. Al-Marhoun correlation

Using equation (7), we have the comparison results shown in Figure 4.

e. Petrosky & Farshad correlation

Using equations (8) and (9), we have the predicted results versus measured results of BPP, shown in Figure 5.

Machine learning algorithms

a. Artificial Neural Network (ANN)

Using Google Colab with the Keras library, we have the BPP comparison results shown in Figure 6.

b. K-Nearest Neighbors (KNN)

Using the KNeighborsRegressor function in Google Colab, we have the BPP predicted results versus measured results, shown in Figure 7.

c. Decision Tree (DT)

Using the DecisionTreeRegressor function in Google Colab, we have the BPP comparison results shown in Figure 8.

d. Group Method of Data Handling (GMDH)

Using Google Colab with Keras library, we have the BPP predicted results versus measured results, shown in Figure 9.

Compare results

Table 3 summarizes the statistical results for estimating bubblepoint pressure by using the regression model's metrics, which include: mean squared error, square root of mean squared error, coefficient of determination. The results show that the GMDH has the highest R^2 (0.9228) and low MSE and RMSE (336605.4 and 580.177).

Trend Analysis

Trend analysis (TA) is a method to study the relationship between features and prediction targets. TA can also identify key relationships between input parameters and p_b predicted values and identify the most robust model. In this study, four input parameters R_s, γ_g, API and T_f were selected to perform TA.

a. Trend analysis for gas solubility

With $T = 102\ ^o$F, $API = 28.3$, $\gamma_g = 0.996$, and R_s taken from a data set of 567 points, the trend analysis for gas solubility is shown in Figure 10.

Most models show that as R_s increases, p_b also increases; only in the model by Al-Marhoun correlation with a low R^2 value display predicted values of p_b much different from the other models, and the graph line has many zigzags. The trend displayed by the GMDH model shows a rigorous relationship between the parameter for trend analysis and the model's predicted values. At the same time, the predicted values versus R_s of the GMDH model are a straight, continuously increasing line with smooth form.

b. Trend analysis for oil API gravity

With $R_s = 226$ (SCF/STB), $T = 102\ ^o$F, $\gamma_g = 0.996$, and API taken from a data set, the result is shown in Figure 11.

Most models show that as API increases, p_b decreases, except the Al-Marhoun model. The GMDH model shows this trend clearly with a straight, continuously decreasing line.

c. Trend analysis for temperature

With $R_s = 226$ (SCF/STB), $API = 28.3$, $\gamma_g = 0.996$, and T taken from a data set, the trend analysis for temperature is shown in Figure 12.

Typical, all models show that as temperature increases, p_b increases. However, some models exhibit a

Table 2: Descriptive statistics for experimental PVT data used in the study

Parameter	Temperature (F)	Solution gas oil ratio (SCF/STB)	API	Gas specific gravity	Bubble point pressure (psi)
Mean	193.86	636.92	35.10	1.1976	1931.97
Standard deviation	51.99	405.76	6.00	0.4554	1261.45
Variance	2698.71	164349.73	35.93	0.2070	1588447.71
Minimum	74.00	26.00	19.40	0.1590	79.00
Maximum	306.00	2496.00	56.50	3.4445	6741.00

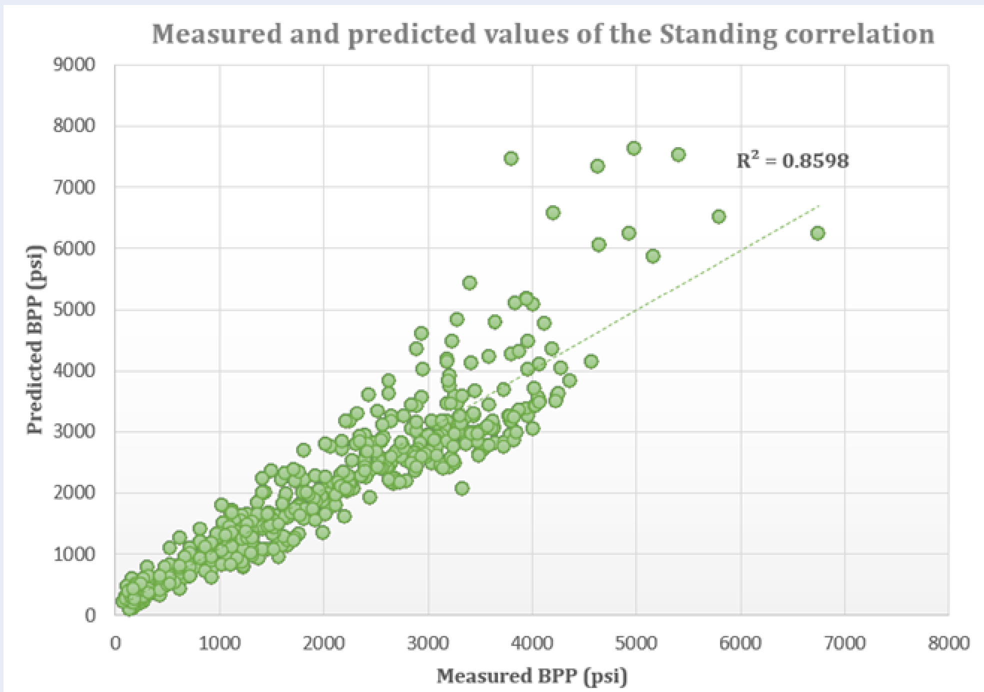

Figure 1: Measured and predicted values of the Standing correlation.

Table 3: Summary of the statistical results for estimating bubblepoint pressure

Model	MSE	RMSE	R^2
Standing	251165	501	0.8498
Vazquez & Beggs	354078	595	0.8460
Glaso	280723	530	0.8526
Al-Marhoun	2044426	1430	0.4706
Petrosky & Farshad	6096167	2469	0.8058
ANN	441419	664.394	0.737
KNN	420474	648.440	0.7947
DT	355461.982	596.206	0.788
GMDH	336605.4	580.177	0.9228

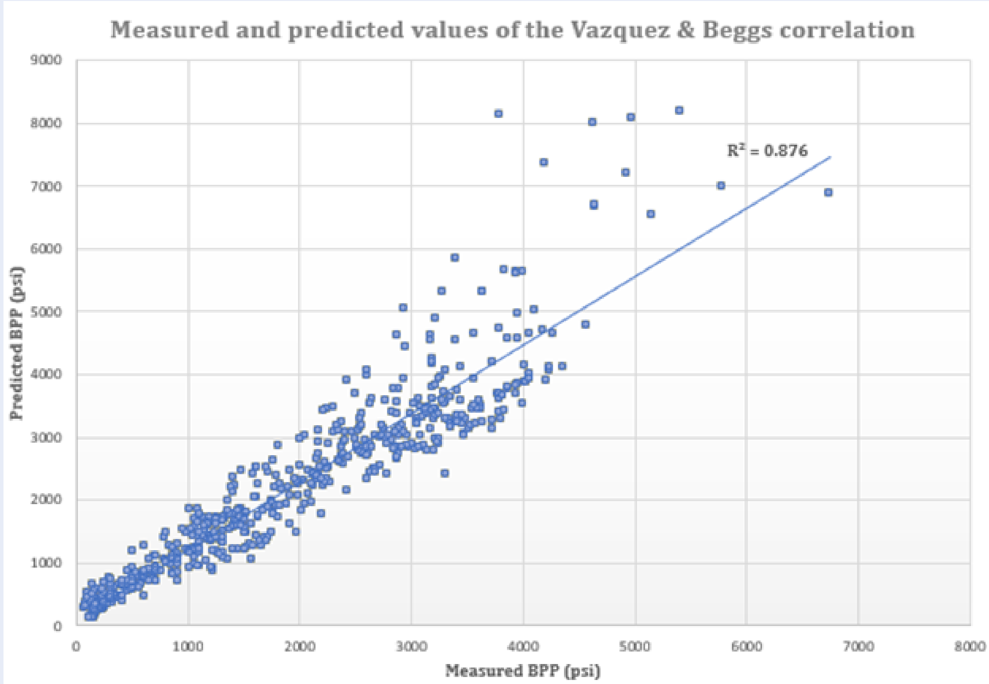

Figure 2: Measured and predicted values of the Vazquez & Beggs correlation.

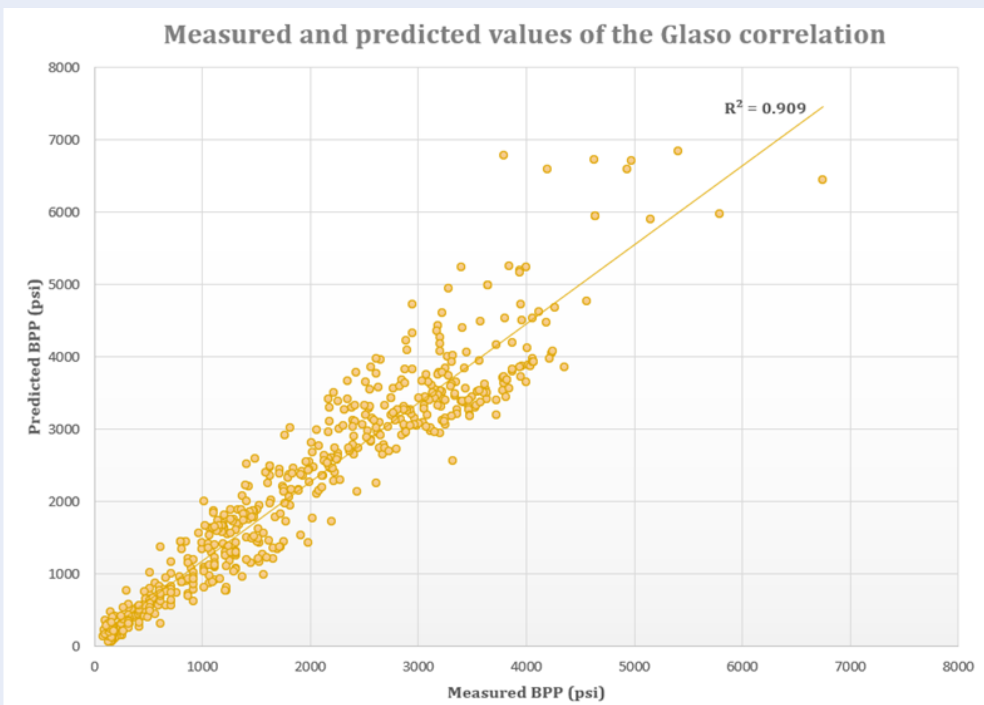

Figure 3: Measured and predicted values of the Glaso correlation.

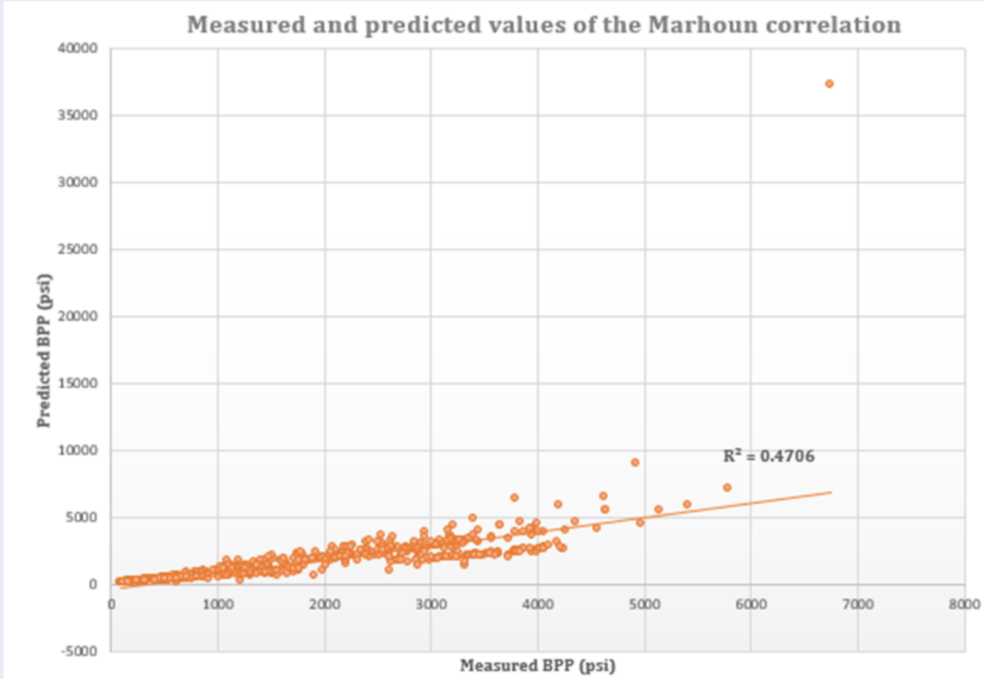

Figure 4: Measured and predicted values of the Marhoun correlation.

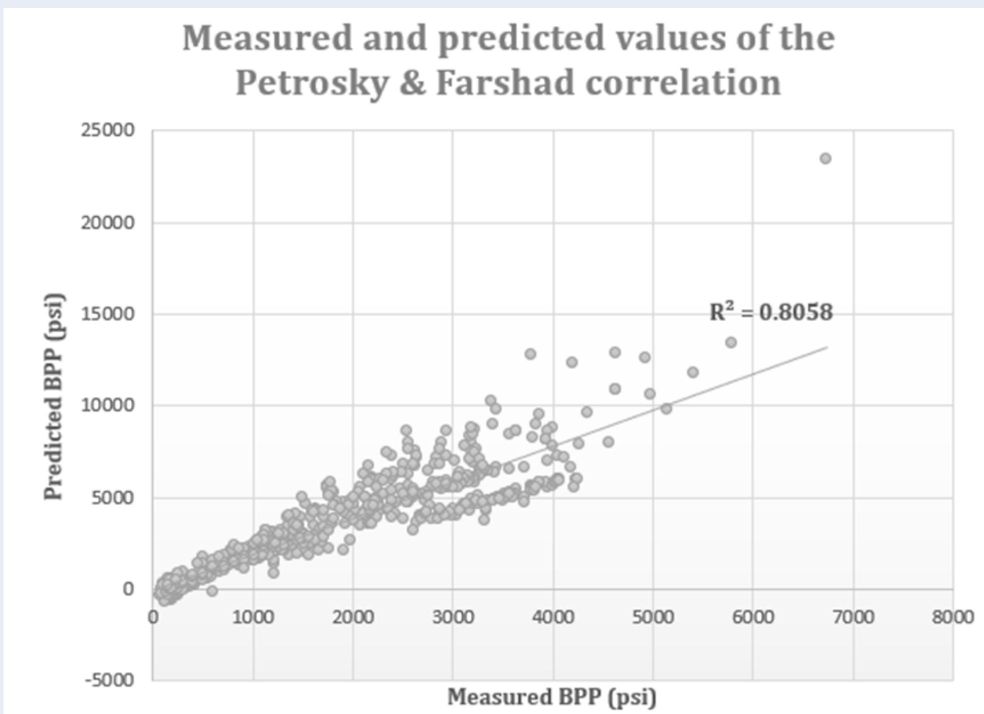

Figure 5: Measured and predicted values of the Petrosky & Farshad correlation.

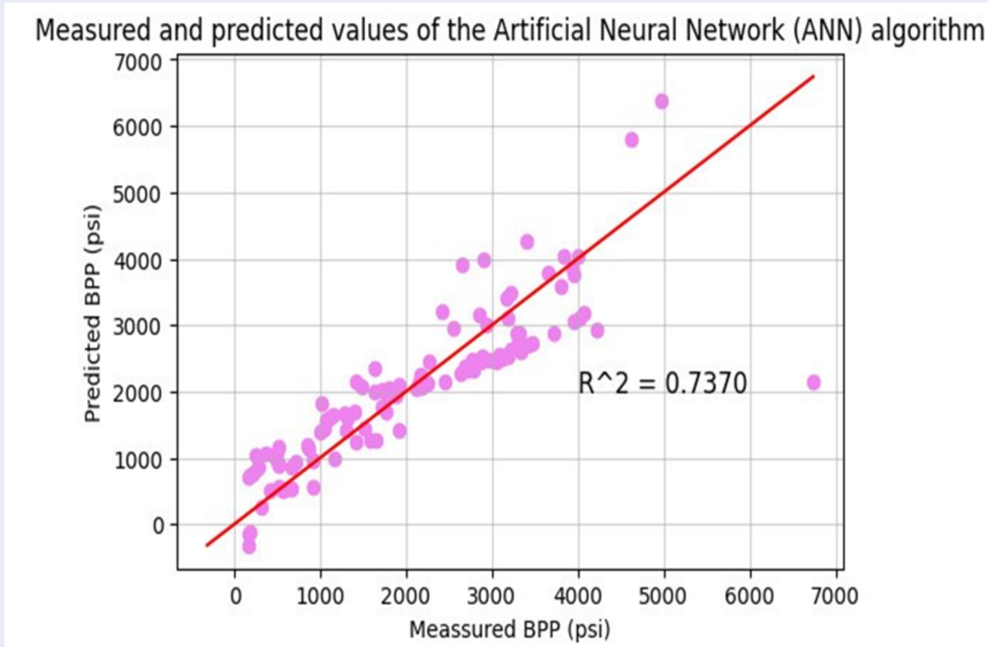

Figure 6: Measured and predicted values of the ANN algorithm.

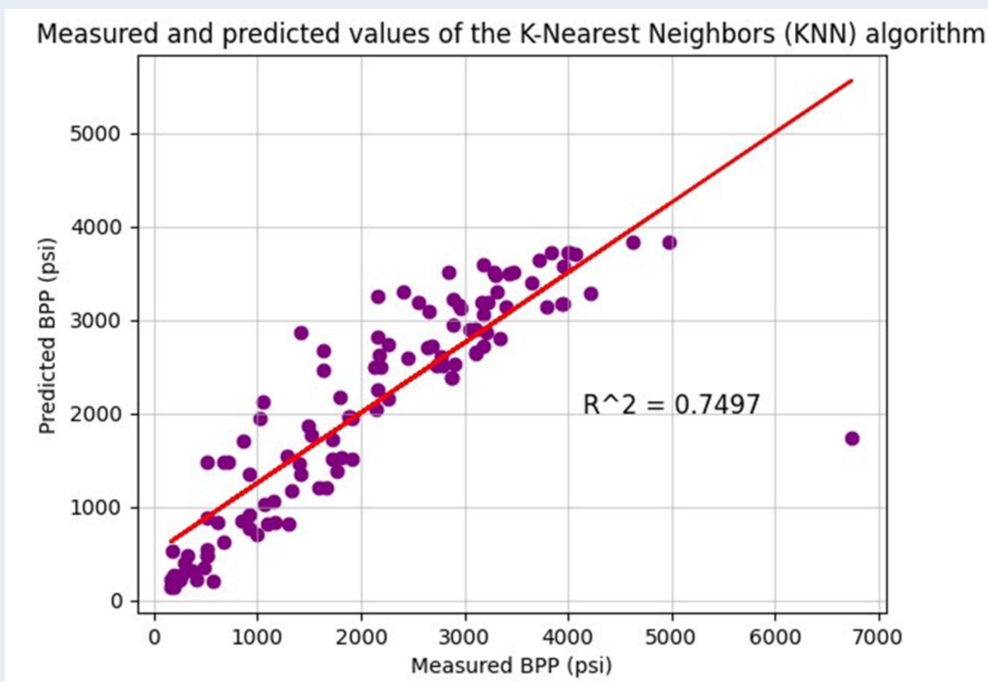

Figure 7: Measured versus predicted values of the KNN algorithm.

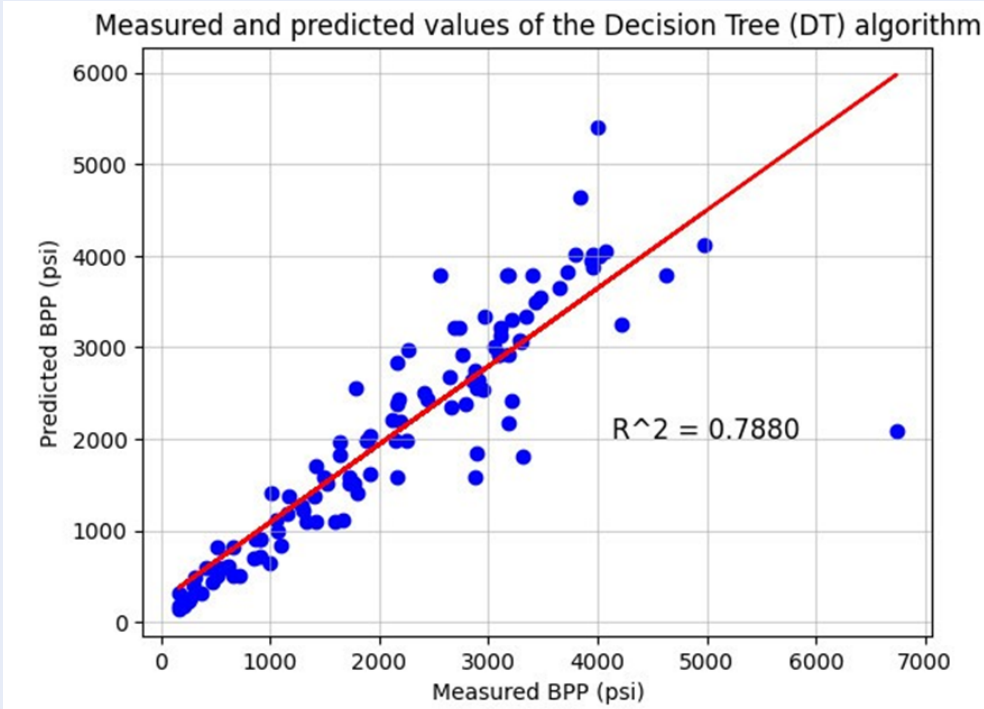

Figure 8: Measured and predicted values of the DT algorithm.

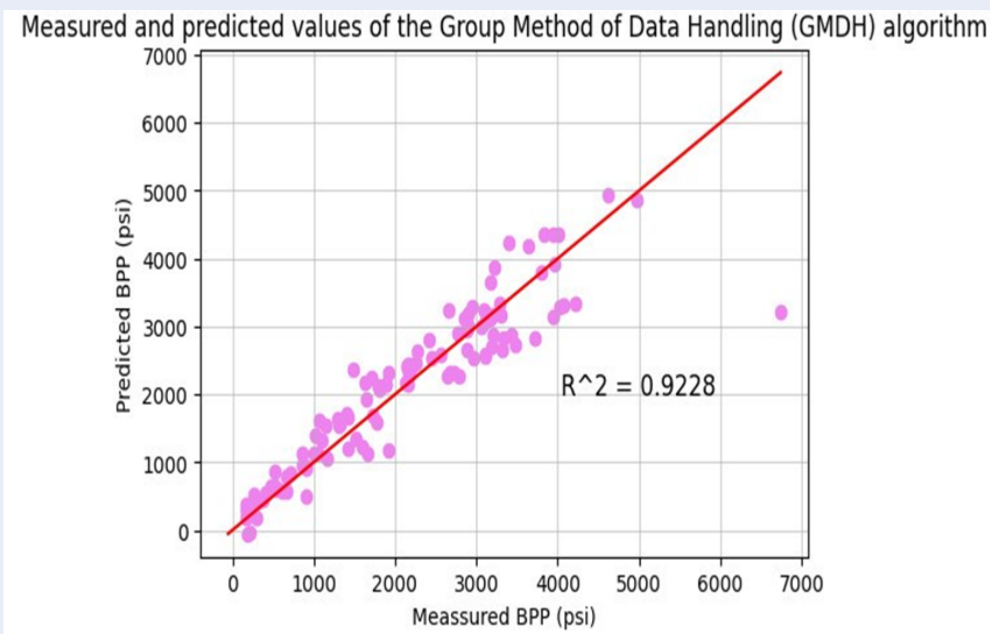

Figure 9: Measured and predicted values of the GMDH algorithm.

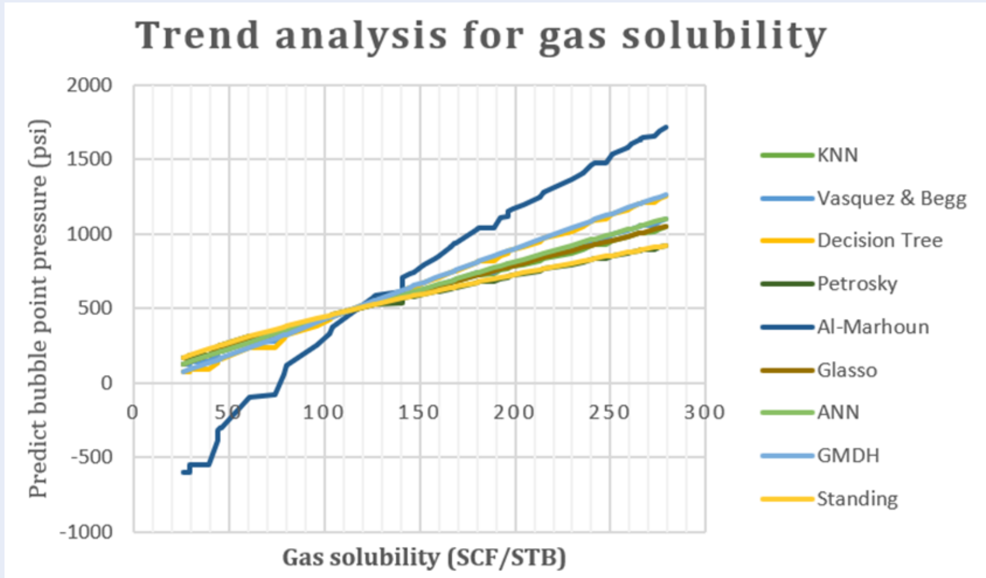

Figure 10: Trend analysis for gas solubility.

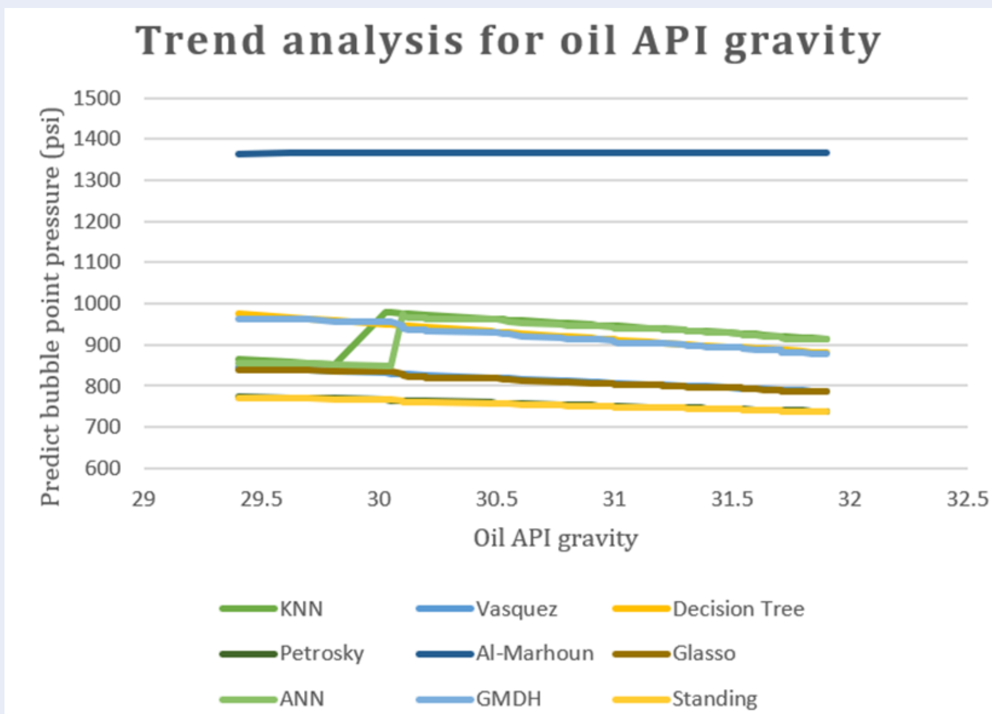

Figure 11: Oil API gravity's trend analysis.

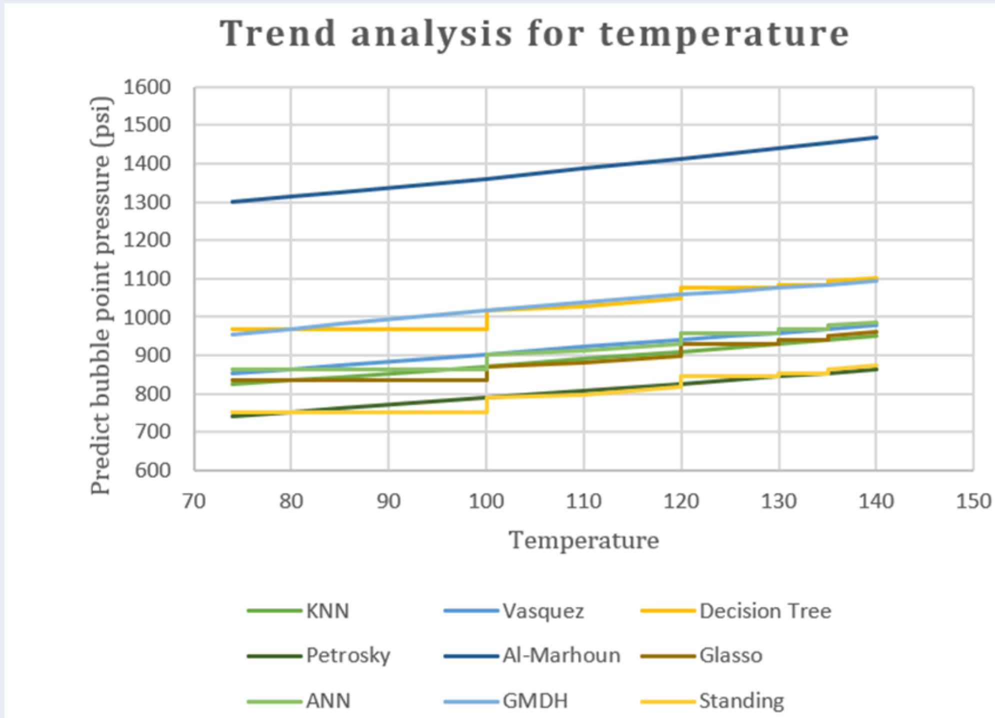

Figure 12: Trend analysis for temperature.

stepped form, and the Al-Marhoun model is far apart from the group of other models.

d. Trend analysis for gas specific gravity

With R_s = 226 (SCF/STB), API = 28.3, T = 102 ^{o}F, and γ_g taken from a data set, the trend analysis for gas specific gravity is shown in Figure 13.

Basically, all models show that as gas specific gravity increases, p_b decreases, but some models exhibit a graph line in a slightly winding form.

CONCLUSIONS

In this study, a dataset with 567 data points on crude oils at some geographical location in the world with four input parameters (R_s, γ_g, API, and T) was used to estimate crude oil bubblepoint pressure (p_b) by two main approaches: empirical correlations and machine learning algorithms. The result shows that the GMDH algorithm is the model that gives the best estimation for bubblepoint pressure.

In addition, trend analysis of input parameters also shows that GMDH graph lines tend to be stable. This strongly confirms that the GMDH model is highly reliable in bubblepoint pressure estimation and can be used for the calculation of other crude oil PVT data sets. The authors suggest that further research on the overfitting phenomenon is needed to increase the reliability of model selection.

CONFLICT OF INTEREST

The authors confirm that there are no conflicts of interest associated with this study.

AUTHOR CONTRIBUTION

Tran Nguyen Thien Tam designed the research, collected data, and wrote the manuscript. Do Pham Minh Huong performed the calculations. Hoang Trong Quang drawn the figures. All authors discussed the results and contributed to the final manuscript.

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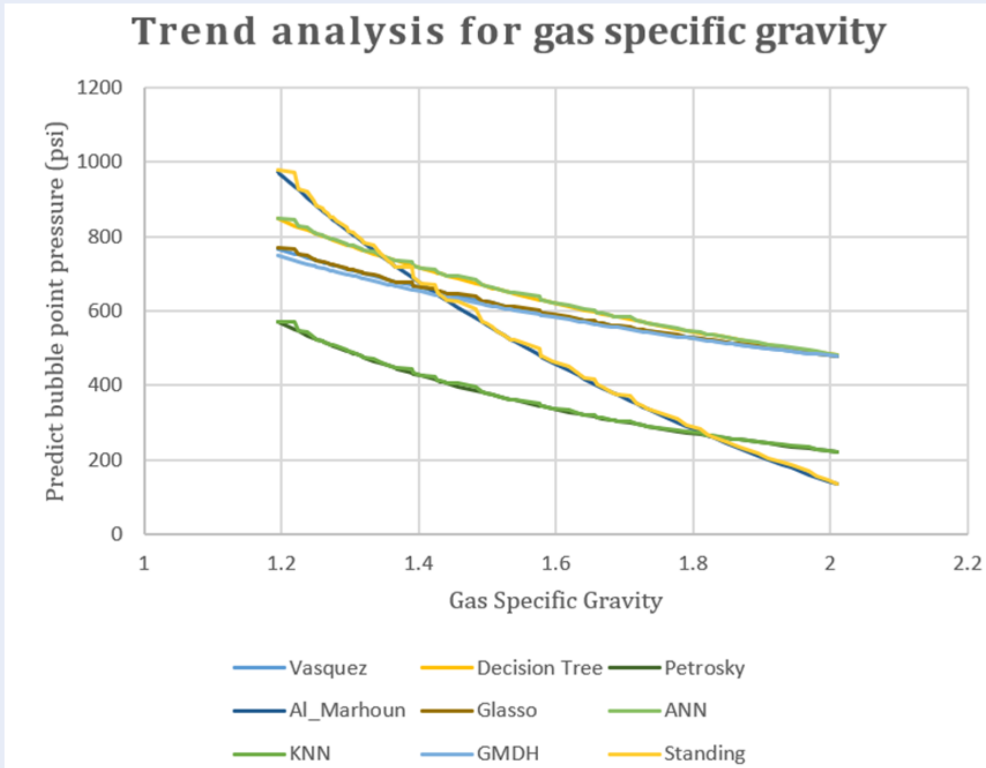

Figure 13: Trend analysis for gas specific gravity.

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Bài nghiên cứu

Ứng dụng phương pháp học máy để ước lượng áp suất điểm bọt cho dầu thô thế giới

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TÓM TẮT

Áp suất tại đó bong bóng khí đầu tiên thoát ra khỏi dầu vỉa chứa được gọi là áp suất điểm bọt. Thông số này ảnh hưởng đến dòng chảy đa pha trong đường ống và hệ số thu hồi dầu từ vỉa chứa. Do đó, điều quan trọng là phải ước tính chính xác áp suất điểm bọt dầu thô. Đã có rất nhiều nghiên cứu về tính toán áp suất điểm bọt từ dữ liệu trong phòng thí nghiệm, có thể tóm lược thành hai cách tiếp cận chính: tương quan thực nghiệm và thuật toán học máy. Trong nghiên cứu này, các tác giả thực hiện tính toán theo cả hai cách tương quan thực nghiệm và thuật toán học máy với Cây quyết định (DT), K láng giếng gần nhất (KNN), Mạng nơron nhân tạo (ANN) và Phương pháp xử lý dữ liệu nhóm (GMDH). Dữ liệu được thu thập từ các tài liệu đã công bố về dầu thô thế giới. Kết quả ước lượng của hai cách tiếp cận trên được so sánh bằng các tham số đánh giá mô hình hồi quy bao gồm: sai số toàn phương trung bình (MSE), căn bậc hai của sai số bình phương trung bình (RMSE) và hệ số xác định (R^2). Kết quả cho thấy thuật toán GMDH cho dự đoán chính xác với MSE và RMSE thấp (336605,4 và 580,177) và R^2 cao nhất (0,9228). Phân tích xu hướng được thực hiện để tăng tính tin cậy cho việc lựa chọn mô hình. Ảnh hưởng của các thông số đầu vào đến kết quả dự đoán chỉ ra rằng mô hình GMDH có độ ổn định cao nhất. Vì vậy, mô hình GMDH được lựa chọn để ước lượng áp suất điểm bọt của dầu thô.

Từ khoá: tương quan áp suất điểm bọt, cây quyết định, k láng giếng gần nhất, mạng nơron nhân tạo, phương pháp xử lý dữ liệu nhóm

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