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A Review of AI and Machine Learning Techniques in Dew Point Pressure Prediction for Gas Condensate Systems

Review paper

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Abstract:

Condensate gas reservoirs pose considerable management challenges due to their intricate phase behavior and the critical need for accurate predictions of dew point pressure (PDew). A precise determination of PDew is vital for optimizing production strategies, estimating reserves, and planning enhanced oil recovery operations. Traditional methods for PDew determination often involve experimental analyses that can be both costly and time-consuming, highlighting the necessity for alternative predictive models. This review consolidates recent advancements in methodologies for predicting PDew, encompassing empirical correlations, equation-of-state models, and cutting-edge artificial intelligence techniques such as neural networks and machine learning algorithms. Key studies discussed demonstrate that AI can significantly enhance the accuracy of PDew predictions through the application of genetic programming (GP), artificial neural networks (ANNs), and XGBoost across a variety of reservoir conditions. These advanced computational methods hold promising potential for improving reservoir characterization and management practices in gas condensate fields.

Keywords: Dew Point Pressure (PDew), Gas Condensate Reservoirs, Phase Behavior Artificial Intelligence (AI) Models, Reservoir Characterization, Enhanced Oil Recovery (EOR)

Introduction

Gas condensate is a type of gas reservoir, typically under pressures below 2,000 psia and temperatures under 100°F, though it can occur at higher pressures and temperatures. Advances in deep drilling techniques have led to the discovery of reservoirs with elevated temperatures and pressures (Sadeq, 2018)[32] Ali, J., et al. (1997) [3]. These reservoirs hold significant gas reserves and considerable quantities of low-density, high-API quality condensate. As production occurs and the pressure in the reservoir declines, heavier components of the gas stream begin to condense into droplets; these droplets gather at the bottom of the wellbore where the pressure drop is most significant, resulting in a relatively low bottom hole flowing pressure (BHFP) (Ganie 2019)[17].

Both references point to the physical state of gas under specific temperatures and pressures, defined by Al-Dhamen and Al-Marhoun (2011)[1], stating that the critical temperatures in gas condensate reservoirs are lower than the reservoir temperature, while cricondentherms are always higher than the temperatures present within the reservoir conditions. During the initial stages of production, if the reservoir pressure exceeds the dew point pressure (PDew) and functions as a single-phase system, it facilitates the efficient separation of valuable condensates at the surface. When the reservoir pressure decreases during a depletion test, it enters a two-phase region where heavier components start to separate from the gas phase, subsequently causing the condensate to become trapped as a residuum, which includes valuable intermediate components (Haji-Savameri et al., 2020)[22].

As the process of depressurization continues, liquid condensate gathers in the reservoir, leading to the formation of free liquid. However, there is typically insufficient permeability to enable effective liquid production (Al-Dhamen and Al-Marhoun, 2011)[1]. Gas condensate reservoirs usually present a gas-to-liquid ratio between 3.2 and 150

MCF/STB (Al-Dhamen and Al-Marhoun, 2011; Haji-Savameri et al., 2020)[1,2, 22]. In such reservoirs, productivity commonly diminishes when the pressure close to the wellbore drops below the dew point pressure (PDew). The accumulation of condensate causes a partial blockage, which impedes the movement of gas around the well, ultimately leading to a decrease in effective gas permeability (Elsharkawy, 2002; Haji-Savameri et al., 2020).

The specific characteristics of reservoir fluids, especially Pressure Volume-Temperature (PVT) data, are crucial for reservoir engineering calculations, such as estimating reserves and devising future Enhanced Oil Recovery (EOR) strategies (Gonzalez et al., 2003)[21]. In gas condensate reservoirs, there are two dew point pressures (PDew). The lower dew point pressure generally falls below atmospheric pressure and is typically not a major concern, as it remains significantly lower than the reservoir pressure. In contrast, identifying the upper dew point pressure—referred to as the retrograde dew point—is essential for effective reservoir management. This research highlights the upper PDew, which is attained when pressure decreases. Gas condensate reservoirs have a lower presence of heavier hydrocarbons compared to oil reservoirs, leading to a shift of the critical point further down and to the left within the PT envelope, resulting in a denser PT diagram (Al-Dhamen and Al-Marhoun, 2011; Haji-Savameri et al., 2020)[1,22].

Therefore, the gas extracted from the reservoir has fewer valuable components, as these components are segregated within the reservoir and close to the wellbore. Therefore, the precise and timely prediction of the dew point pressure (PDew) is vital for fluid characterization, assessing reservoir performance, planning for the development of gas condensate reservoirs, and designing and optimizing production systems. Although determining PDew through experimental methods yields the most accurate and trustworthy results, it can also be an expensive and time-consuming endeavor, often accompanied by the risk of errors (Elsharkawy, 2002).[13]

2- Hydrocarbon reservoir

Various definitions have been suggested to categorize reservoirs to comprehend their characteristics and thermodynamic responses during the initial phases of field development {1}. A traditional definition that focuses on fluid phase behavior is as follows:

1- Heavy Oil
2- Black Oil
3- Volatile Oil
4- Gas Condensate
5- Dry Gas
6- Asphalts-Bitumen
7- Oil Sands

The conditions of the reservoir, including temperature, pressure, and fluid composition, play a vital role in determining the category of the fluid. The phase envelope can differ in classification depending on the pressure at a given reservoir temperature, as demonstrated in Fig. 1.

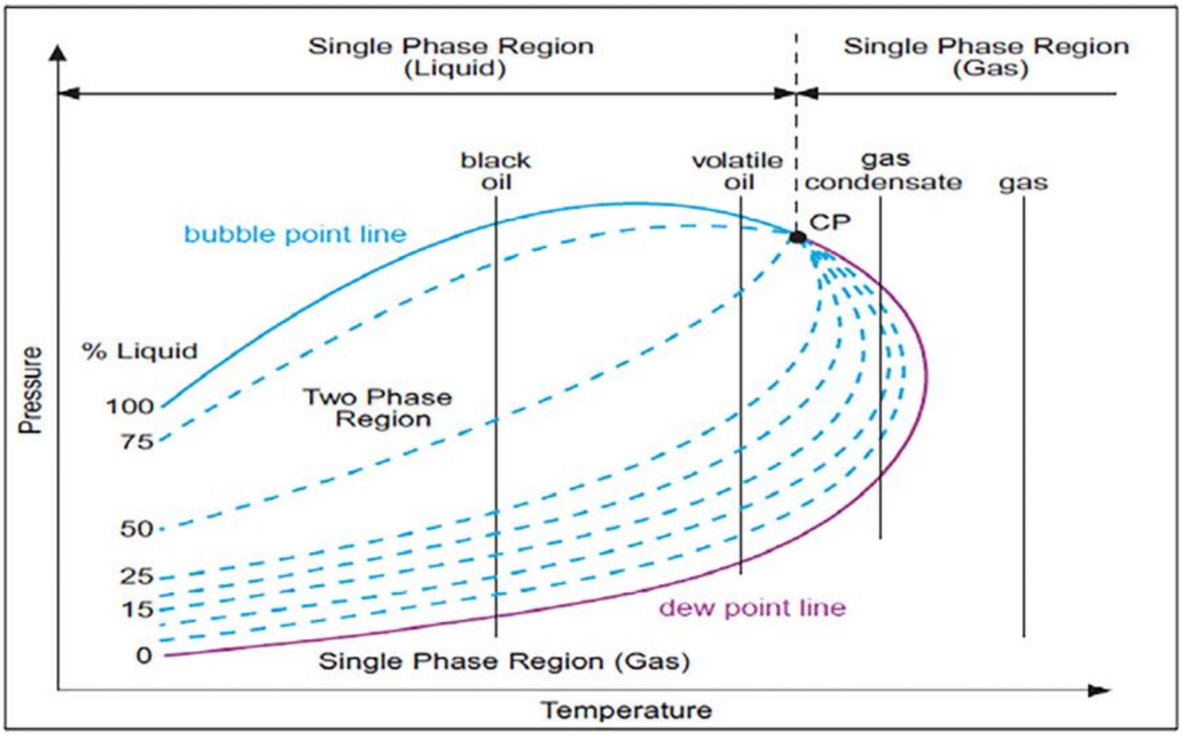

Fig (1) P-T diagram of different hydrocarbon reservoir (Echenique, 2016) [10]

Flow region

The flow characteristics of gas condensate reservoirs have been discussed by various researchers during the depletion stage when the bottom hole pressure (BHP) falls below the dew point pressure. Furthermore, the classification of different flow regions has been reported. Three specific regions can be illustrated and explained in Fig. 2. Economides, M., et al. (1987) [11]

First Region: Adjacent to the wellbore is a two-phase gas-condensate reservoir that contains both flowing condensate and gas. The pressure (Pr) is underneath the dew point pressure (Pdew), and the saturation conditions indicate that the condensation saturation is less than the critical saturation levels. Consequently, Pr decreases as it approaches the well and falls below Pdew, resulting in the establishment of a condensate bank.

Second Region: The middle region, which serves as the second one, exists between the first and third regions as a two-phase gas-condensate reservoir with mobile gas and stationary condensate (Pr<Pdew & Soc>So) since the condensation saturation is lower than the critical condensate saturation [14]. Thus, Pr decreases toward the well and eventually becomes less than Pdew, causing the condensate bank to begin forming. Fevang, O. (1995) [15]

Region 3 is the stone of the reservoirs, a single-phase gas reservoir (Pr>Pdew). A fourth region may exist in the immediate well vicinity and has the same conditions as the region one but with high gas relative permeability.

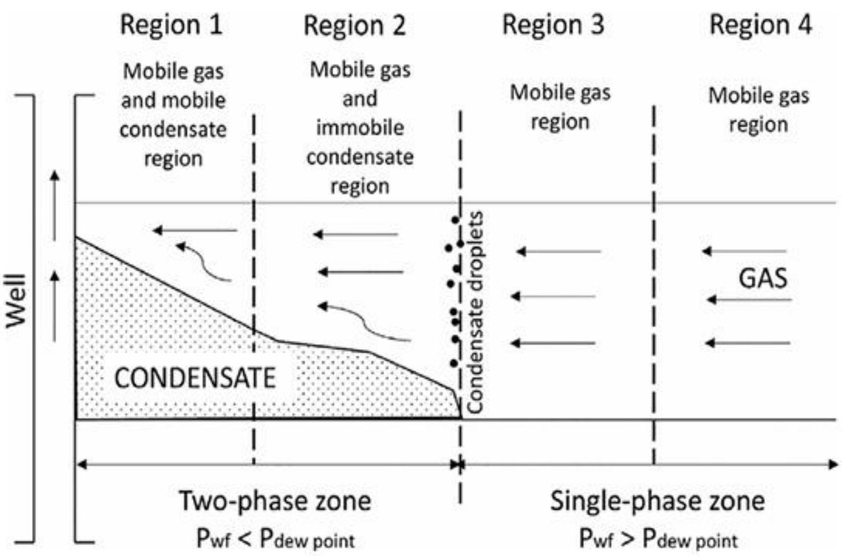

Fig (2) Flow region development (Fevang, 1996) [16]

Fig (2) development of fourth region (Ganie, 2019)[17, 18]

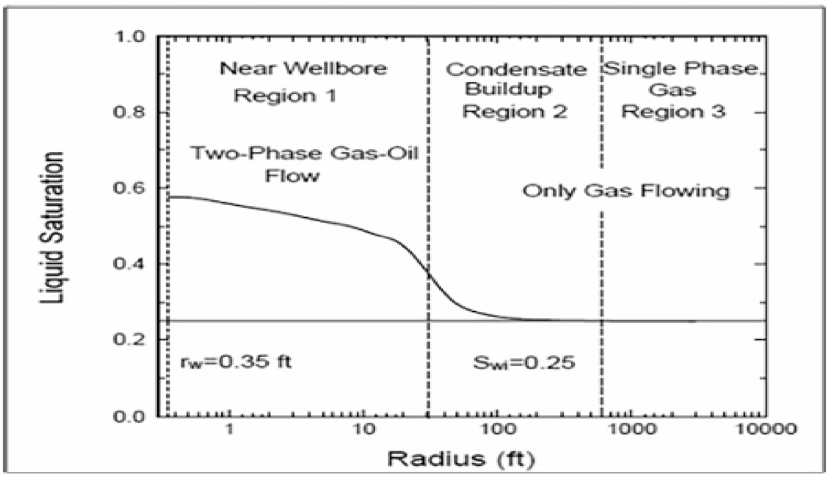

Fig.3 implements the existence of the fourth region.

3- Dew point pressure measurements in gas condensate reservoirs

Dew point pressure measurements in gas condensate reservoirs by experimental methods

FIGURE 3

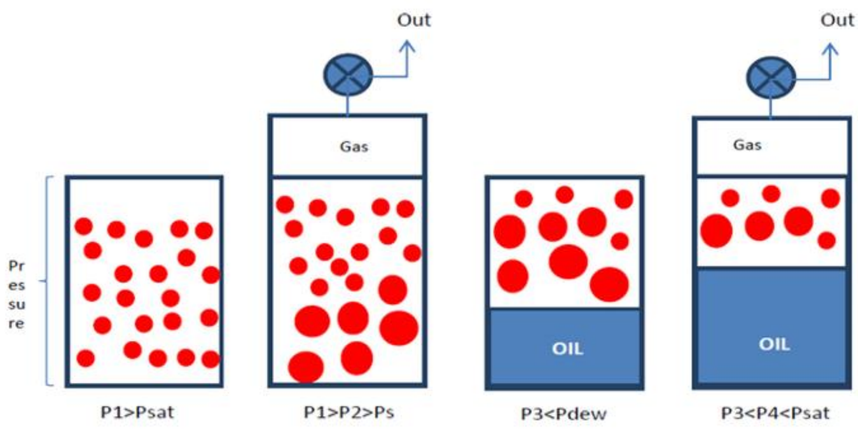

Fig (4) CCE experiments (16)

Traditionally, three laboratory experiments of (PVT) on reservoir fluids exist. These experiments are the constant composition expansion (CCE), differential liberation experiment (DLE), and constant volume depletion (CVD). To characterize and understand the reservoir fluids behavior, these experiments are set. PVT in gas condensate reservoirs is different from oil, only CVD and CCE are required. the heavy fraction of fluid is anatomized to characterize mayor components by extended carbon groups (Danesh, 1998).[9]

Constant Composition Expansion (CCE):

This laboratory experiment is used to compute the dewpoint pressure (Pdew), Z factors of single-phase gas, and the condensation dropout curve at P < Pdew which is oil relative volume. Fig. 4 illustrates the procedure of this experiment

Constant Volume Depletion (CVD): This experiment is a substantial test for gas condensate fluids. Reservoir pressure vs. produced–well stream composition and surface products, liquid dropout, and re-vaporization that occurs during pressure depletion, among others, all these data can be provided by this experiment and used directly by an engineer. Fig. 5 presents the process of CVD

3-2 Dew point pressure measurements in gas condensate reservoirs by empirical correlations

Several methods for the prediction of the gas condensate pressure dew point (PDew) have been proposed, such as correlations based on Artificial Intelligence (AI), equations of state (EoS), graphical approaches, and experimental techniques, as depicted above. Eilerts and Smith (1942) [12] correlated PDew with temperature (T), composition, molal average boiling point, and oil-to-gas

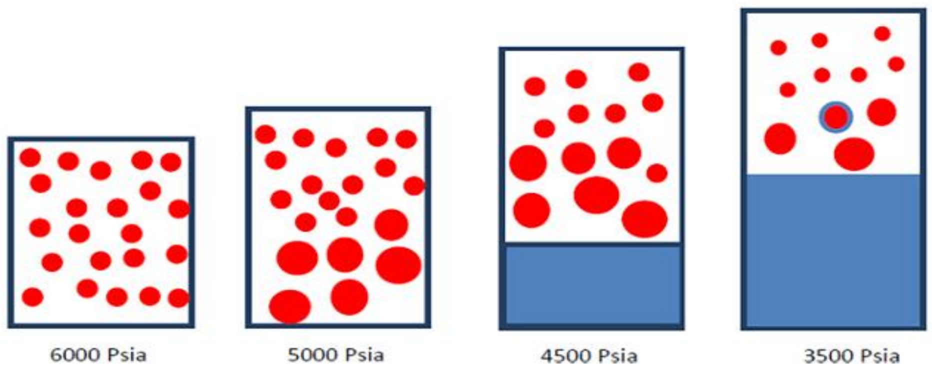

Fig (5) CVD experiments (16)

volume ratio. Olds et al. (1945) studied fluid samples from the Paloma field and reported that composition affects PDew and that the removal of intermediate fractions increases PDew. In another study on samples from San Joaquin Valley fields, the same authors developed a plot of PDew as a function of Gas Oil Ratio (GOR), T, and oil API gravity (Olds et al., 1949).[28] Reamer and Sage (1950a) [31]tried to extend existing correlations to higher values of GOR with samples taken from a field in Louisiana.

Organick and Golding (1952) [29] proposed a correlation based on the direct dependence of saturation pressure on composition, where the indicators of composition are the molal average boiling point and a modified weight average equivalent molecular weight. Later, Nemeth (1966) [26] and Nemeth and Kennedy (1967) [27] developed a correlation to estimate PDew as a function of composition, temperature (T), and description of C7+. Crogh (1990)[8] improved the relation developed by Nemeth (1966) [26]by relating the composition of a retrograde gas-condensate mixture to its composition at the dew point pressure (PDew). Further, Potsch and Braeuer (1996) [30] proposed a graphical method for determining the PDew, which exhibited a relative accuracy of less than 3% or a maximum deviation of 5 bars. Carlson and Cawston (1996) [6] found that the H_2S concentration affects the dew point pressure (PDew), Coats, K. H. (1980) [7] that is, as the H_2S concentration increases, the amount of liquid dropout decreases. Yisheng (Fang et al., 1998) [14] proposed a relation based on gas condensate sample data taken in western China that is a function of the composition, temperature, and average molecular weight of the mixture fluid with an average error of less than 5.8%.

Humoud and Al-Marhoun (2001) [23] proposed a correlation to predict PDew based on T, pseudo-reduced P and T, primary separator GOR, primary separator P and T, and relative densities of separator gas and C7+ fraction using field and laboratory PVT analyses data of samples representing gas reservoirs in the Middle East.

Elsharkawy (2001, 2002)[13] proposed an empirical correlation to predict PDew for gas condensate samples using routinely measured gas composition and T, proving its superiority over EoS-based models. Marruffo et al. (2002) [25] developed a new correlation to predict PDew using 54 data samples and reported an error of 5.74%. They utilized C7+

content, Gas Condensate Ratio (GCR), API gravity, and T as input parameters. When comparing their proposed correlation with the one by Nemeth (1966) [26] , they demonstrated its superiority.

3-1 Dew point pressure measurements in gas condensate reservoirs via AI applications

In 2003, Gonzalez et al. utilized a Neural Network (NN) model to predict the PDew of retrograde gas reservoirs, using 802 experimental Constant Volume Depletion (CVD) data and reported an average absolute error of 8.74%. In 2007, Jalali et al.[24] used 111 data samples to develop different Artificial Neural Networks (ANNs) for predicting PDew and concluded that the Levenberg-Marquardt training algorithm provided the best results.

In 2011, Al-Dhamen [1]and Al-Marhoun developed various models including nonlinear multiple regression, non-parametric regression model (Alternating Conditional Expectations (ACE) technique), and ANN using a total of 113 data samples obtained from Constant Mass Expansion (CME) tests collected from Middle East fields. The ANN model yielded the best results.

In 2012, Godwin [19] proposed a new correlation to predict the gas condensate's PDew using 259 data samples and claimed the developed correlation's superiority compared with existing correlations. In 2017, Alzahabi et al. (2017) [5] proposed a correlation based on down-hole fluid analysis data. They used multiple linear regression and utilized 667 data samples to develop their model.

Shokir, Eissa M. El-M (2008) [33] presents a genetic programming (GP) and Orthogonal Least Squares (OLS) algorithm designed to predict dew point pressure (DPP) in gas condensate reservoirs. The model estimates DPP based on reservoir fluid composition—including the molar fractions of methane to heptane-plus, nitrogen, carbon dioxide, hydrogen sulfide, and the molecular weight of the heptane-plus fraction—alongside reservoir temperature. Utilizing data from 245 experimental gas condensate systems, the model was validated against existing correlations. The results show that the GP-OLS model achieved superior accuracy, with an average absolute relative error (AAER) of just 4.2%. This research underscores the importance of precise DPP prediction for effective reservoir management and illustrates the robustness of the GP-OLS method when experimental data is lacking.

AL-Jawad, M. S. and O. F. Hasan, et al. (2012) [4] examine methods for estimating dew point pressure in Saudi Arabian gas condensate fields using artificial intelligence (AI) techniques. The study highlights the critical role of dew point pressure in reservoir evaluation and the difficulties of direct measurement from fluid samples. Comparing traditional methods—such as those by Nemeth and Kennedy[27] , and Elsharkawy [13] —with AI models like Multilayer Perceptron (MLP), General Regression Neural Networks (GRNN), Radial Basis Function (RBF) networks, Support Vector Machines (SVM), and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), the researchers assess these models using data from 98 PVT reports, focusing on Mean Absolute Percentage Error (MAPE) and Coefficient of Correlation (R). The findings indicate that GRNN is particularly effective, showcasing the potential of AI models to improve accuracy and computational efficiency in predicting dew point pressure, thereby enhancing reservoir management in complex gas condensate fields.

Alzahabi et al. (2017) [5] presented a novel model to predict the dew point pressure of gas condensate reservoirs using down-hole fluid analyzer data without performing detailed laboratory analysis or surface fluid data. The dataset used in this work consists of 667 samples of gas condensate. The model incorporates parameters such as temperature, CO_2, CH_4, and other hydrocarbon mole fractions. Applying such modern techniques of statistical analysis as multiple linear regression and model selection criteria in the form of AIC and BIC, the study accomplished a mean absolute relative error of 2% in the prediction of logarithmic values of pressure. The validation via K-fold cross-validation showed strong predictive abilities, compared with other advanced methodologies like random forests. The model has practical implications because it can be used in real-time, assessing dew-point pressure during down-hole fluid sampling to manage the reservoir and well design in gas condensate fields. Herein, this approach epitomizes one of the major recent advances in reservoir engineering by providing reliable estimates critical in optimizing production strategies without conventional laboratory-related constraints.

A new predictive model for dew point pressure (Pd) in gas condensate reservoirs by using

Gene Expression Programming (GEP) coupled with non-linear regression analysis. This approach will clearly explain the complex interactions between key parameters such as reservoir temperature, hydrocarbon composition, heptane-plus fractions, and nonhydrocarbon components like CO2 and N2. The model was trained on a data set of 453 published data points and then was validated by analyzing 27 additional gas condensate samples, which cover wide ranges in PVT properties studied under constant composition expansion (CCE) experiments. A statistical comparison with current empirical correlations proves the better performance of the GEP-based model, which features low average relative errors and high coefficients of determination (R^2). The proposed model gives a robust alternative for Pd prediction, especially where full PVT data is unavailable. In this respect, it would be an excellent tool among the basic reservoir engineering and management tools for optimizing production techniques and fluid characterization. The study has improved upon the accuracy of dewpoint pressure prediction with an added advantage over traditional empirical models by overcoming their weaknesses and including advanced computational techniques.

An extensive research on dew point pressure prediction for gas condensates using an advanced machine learning technique called XGBoost, which can overcome the challenges related to the accurate prediction of DPP.
They analyzed a dataset of 342 samples, where they carefully checked and transformed the variables into composition data, the reservoir temperature, and the specific gravity of heptane-plus. They also built a robust predictive model by using XGBoost with engineering features—artificial proxy features and pseudocritical properties derived from Sutton's correlations. Compared to the classical empirical models developed by Nemeth and Kennedy (1967) [27] , Elsharkawy (2001)[13] , Ahmadi and Elsharkawy (2016), [10] and Gomaa, S. et al. (2018) [20], the XGBoost model showed the best performance in predicting the fracture gradient with a mean relative error of 470 psi and a mean absolute relative error of 7.16%. The present study brings out the effectiveness of XGBoost when used on small datasets and its potential to outperform traditional empirical models for DPP forecasting under various gas composition and reservoir condition combinations.

A new modeling approaches for the prediction of dew point pressure of gas condensate (PDew), thus meeting the requirements for accurate predictions in reservoir engineering and, at the same time, decreasing time and costs linked with laboratory measurements. This work, by using a dataset of 721 samples collected over several decades, performed extensive preprocessing steps, including duplicate removal, outlier removal, and transformation to reach the normal distribution. Further, the dataset was grouped according to the hydrogen sulfide concentration (XH2S) before splitting the dataset into training and testing sets. Three different neural network structures, including MLP-NN, RBF-NN, and LSSVM, were optimized and then combined through the CMIS technique. Of these, the harmonic CMIS model performed better with an AARD value of 3.456% and an R^2 coefficient of 0.9702. The present study shed light on the benefits of combining different models in the estimation of PDew, which has important implications in both theoretical study and applied practices in reservoir engineering and optimization of production.

Conclusion:

In short, the review establishes the importance of reliable PDew prediction for effective gas condensate reservoir management. Although the traditional empirical correlations and EoS-based methods have provided foundational insights, their limitations in dealing with complex reservoir conditions drive advancements in AI-driven predictive modeling. Many studies using GP, ANNs, and XGBoost have shown a substantial improvement in the accuracy of PDew prediction over conventional methods, hence providing strong solutions for reservoir engineers. The development of artificial intelligence-driven methodologies not only enhances the forecasting capabilities but also allows for real-time decision-making, hence optimizing production efficiency and resource utilization. Future research efforts should focus on reducing uncertainty in the data sets by drawing more data points, improving algorithmic models, and integrating interdomain strategies to enhance the reliability and applicability of the PDew prediction models within the realm of gas condensate reservoir engineering.

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