Journal Homepage: http://ijcpe.uobaghdad.edu.iq
Iraqi Journal of Chemical and Petroleum Engineering
Vol. 27 No. 1 (March 2026) 143 – 154
EISSN: 2618-0707, PISSN: 1997-4884

# Hybrid particle swarm neural network and regression models for dew-point pressure prediction

**Salem O. Baarimah [a], Ghareb Hamada [b, *], Al-Gathe Abedelrigeeb [a], Khaled Ba-Jaalah [a]**

*a Department of Petroleum Engineering, University of Hadhramout, Al-Mukulla, Yemen*
*b Arab Academy for Science, Technology & Maritime Transport, Alexandria, Egypt*

## Abstract

Accurate prediction of dew-point pressure (DPP) is essential for the development and production management of gas condensate reservoirs; however, existing empirical correlations and standalone machine learning models often suffer from limited generalization and sensitivity to data variability. This study addresses this gap by developing and comparing a nonlinear multiple regression (NLMR) correlation and a hybrid particle swarm optimized neural network (PSONN) model using a large and diverse dataset of 880 experimental samples collected from published literature and Middle East reservoirs. The PSONN model was selected due to its capability to overcome neural network limitations such as slow convergence by optimizing network weights through global swarm intelligence. The hybrid PSONN model achieved superior predictive accuracy with APRE of 2.45% and CC of 0.997, outperforming both the proposed NLMR correlation and previously published models. The results demonstrate that the developed hybrid framework can significantly improve dew-point pressure estimation, thereby supporting reliable reservoir characterization, surface facility design, and production planning in gas condensate fields.

*Keywords: Hybrid; Neural network; Particle swarm; Nonlinear regression; Dew-point pressure.*

*Received on 09/12/2025, Received in Revised Form on 05/03/2026, Accepted on 08/03/2026, Published on 30/03/2026*

*https://doi.org/10.31699/IJCPE.2026.1.12*

## 1- Introduction

Dew-point pressure (DPP) is one of the most important factors for gas condensate fluid. It is often required for developing of gas condensate reservoir [1]. Therefore, a perfect estimation of this property has been the main challenge for gas condensate reservoir. The iterative method or empirical correlations usually use to predict dew-point pressure [2].

Traditionally, DPP has been estimated using empirical correlations and equations of state (EOS) [3]. Although these approaches are widely applied, their accuracy is often limited to the range of data from which they were developed, and they may not generalize well to reservoirs with different compositional characteristics. In addition, EOS-based calculations require complete compositional data and iterative procedures, which may be computationally expensive and sensitive to tuning parameters [4].

In recent years, artificial intelligence (AI) and machine learning (ML) techniques have been increasingly applied to petroleum engineering problems, including DPP prediction [5]. Models such as artificial neural networks (ANN), support vector machines (SVM), fuzzy logic systems, and genetic programming have demonstrated improved predictive capabilities compared to classical correlations. However, standalone ML models may suffer from slow convergence and sensitivity to initial weight selection [6].

Hybrid intelligent systems combine optimization algorithms with learning models to overcome these limitations [7]. Particle swarm optimization (PSO), when integrated with ANN, can optimize network weights globally and improve convergence stability. Despite these advantages, relatively few studies have explored robust hybrid frameworks using large and diverse datasets for DPP prediction [8].

Therefore, this study aims to develop and evaluate two predictive approaches: a nonlinear multiple regression (NLMR) correlation and a hybrid particle swarm optimized neural network (PSONN) model. The objectives are to establish a reliable regression-based correlation, develop a hybrid AI model with improved generalization, and benchmark both models against published correlations and AI models using comprehensive statistical evaluation.

## 2- Literature review

The first published dew-point pressure correlation can be dated back to 1947 by Sage and Olds [1]. Certainly, over the past three decades, there has been a growing interest in developing new correlations for dew-point

*Corresponding Author: Email: ghareb.hamada@aast.edu

pressure obtained from different regions around the world.

These correlations aim to establish relationships between various properties of crude oil, such as density, temperature, API gravity, and other compositional characteristics [1-4]. Some of the most important studies were conducted by Nemeth and Kennedy [9], Humoud and Al-Marhoun [10], Elsharkawy [11], Marruffo et al [12], Shokir [13], Godwin [14], Ahmadi and Ebadi [15], Kamari et al [16], Ahmadi and Elsharkawy [17], and Alarouj et al [18] as follows:

Humoud, and Al-Marhoun [10]:

$$\ln(DPP) = \beta_0 + \beta_1 \ln(T_R) + \beta_2 \ln(R_m) + \beta_3 \ln(P_{SP} \cdot T_{SP}) + \beta_4/T_{\mathrm{pr}} + \beta_5/\mathrm{P_{pr}} + \beta_6/\gamma_{C7+} \quad (1)$$

Where: $\beta_0$ , $\beta_1$ ,$\beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ and $\mathrm{R_m}$ are coefficients. See [10].

Elsharkawy [11]:

$$DPP = A_0 + A_1 T_f + A_2 \mathrm{H_2S} + A_3 \mathrm{CO_2} + A_4 \mathrm{N_2} + A_5 \mathrm{C_1} + A_6 \mathrm{C_2} + A_8 \mathrm{C_4} + A_9 \mathrm{C_5} + A_{10} \mathrm{C_6} + A_{11} \mathrm{C_{7+}} + A_{12} \mathrm{MW_{C_{7+}}} + A_{13} \gamma_{C_{7+}} + A_{14} \left(\mathrm{C_{7+}MW_{C_{7+}}}\right) + A_{15} \left(\frac{\mathrm{MW_{C_{7+}}}}{\gamma_{C_7}}\right) + A_{16} \left(\frac{X\mathrm{C_{7+}MW_{C_{7+}}}}{\gamma_{C_{7+}}}\right) + A_{17} \left(\frac{X\mathrm{C_{7+}}}{(X\mathrm{C_1}+X\mathrm{C_2})}\right) + A_{18} (X\mathrm{C_{7+}}/X\mathrm{C_3} + X\mathrm{C_4} + X\mathrm{C_5} + X\mathrm{C_6}) \quad (2)$$

Where: $\mathrm{A_1}$, $\mathrm{A_2}$, $\mathrm{A_3}$, $\mathrm{A_4}$, $\mathrm{A_5}$, $\mathrm{A_6}$, $\mathrm{A_7}$, $\mathrm{A_8}$, $\mathrm{A_9}$, $\mathrm{A_{10}}$, $\mathrm{A_{11}}$, $\mathrm{A_{12}}$, $\mathrm{A_{13}}$, $\mathrm{A_{14}}$, $\mathrm{A_{15}}$ , $\mathrm{A_{16}}$, $\mathrm{A_{17}}$ and $\mathrm{A_{18}}$ are coefficients [11].

Marruffo et al [12]:

$$\mathrm{DPP} = K1 * \left[\frac{GOR^{K2}}{C_7^{+K3}} * K8 * API^{\left(K4 * Tr^{KS} - K6 * C_7^{KT}\right)}\right) \quad (3)$$

Where: $\mathrm{K_1}$, $\mathrm{K_2}$, $\mathrm{K_3}$, $\mathrm{K_4}$, $\mathrm{K_5}$, $\mathrm{K_6}$, $\mathrm{K_7}$ and $\mathrm{K_8}$ are coefficients [12]

Shokir [13]:

$$DPP = B_1 + B_2 + B_3 + B_4 \quad (4)$$

Where: $\mathrm{B_1}$, $\mathrm{B_2}$, $\mathrm{B_3}$ and $\mathrm{B_4}$, are coefficients [13].

Godwin [14]:

$$DPP = A_0 + A_1 B_1 + A_2 B_2 + A_3 B_3 + A_4 B_4 + A_5 B_5 + A_6 B_6 + A_7 B_7 + A_8 B_8 + A_9 B_9 + A_{10} B_{10} + A_{11} B_{11} + A_{12} B_{12} + + A_{13} B_{13} + A_{14} B_{14} + A_{15} B_{15} \quad (5)$$

Where: $\mathrm{B_1}$, $\mathrm{B_2}$, $\mathrm{B_3}$, $\mathrm{B_4}$, $\mathrm{B_5}$, $\mathrm{B_6}$, $\mathrm{B_7}$, $\mathrm{B_8}$, $\mathrm{B_9}$, $\mathrm{B_{10}}$, $\mathrm{B_{11}}$, $\mathrm{B_{12}}$, $\mathrm{B_{13}}$, $\mathrm{B_{14}}$, $\mathrm{B_{15}}$, $\mathrm{A_1}$, $\mathrm{A_2}$, $\mathrm{A_3}$, $\mathrm{A_4}$, $\mathrm{A_5}$, $\mathrm{A_6}$, $\mathrm{A_7}$, $\mathrm{A_8}$, $\mathrm{A_9}$, $\mathrm{A_{10}}$, $\mathrm{A_{11}}$, $\mathrm{A_{12}}$, $\mathrm{A_{13}}$, $\mathrm{A_{14}}$ and $\mathrm{A_{15}}$, are coefficients [14].

Ahmadi and Ebadi [15]:

$$DPP = \text{-}888.278 - T \times (C1 \times 3.6063 + T \times 0.007856) + C1 \times 1467.87 + A \times 0.98907 \quad (6)$$

Where: A, B, C [15].

Kamari et al [16]:

$$DPP = A + B \quad (7)$$

Where: A and B [16].

Ahmadi and Elsharkawy [17]:

$$DPP = \& - 888.278 - T \times \mathrm{C_1} \times 3.60639 + (T)^2 \times 0.00785623 + \mathrm{C_1} \times 1467.87 + A \times 0.989073 \quad (8)$$

Where: A, B, C [17].

Alarouj et al [18]:

$$DPP = (I_1 + I_2 + I_3 + I_4 + I_5)/145. \quad (9)$$

Where: $\mathrm{I_1}$, $\mathrm{I_2}$, $\mathrm{I_3}$, $\mathrm{I_4}$ and $\mathrm{I_5}$ are coefficients [18].

In recent years, the application of a powerful predictive tool as Artificial Intelligence (AI) and Machine Learning (ML) models has grown continuously in petroleum engineering. Neural Network (NN) model [19] was developed to predict the DPP of condensate gas reservoirs using 802 data samples. Different ANN models [20] were proposed for predicting DPP using 111 data sets. 113 data points were used to develop an ANN technique gathered from Middle East reservoir [21, 22]. The ANN technique obtained the best results. Also, different ANN models were proposed for predicting DPP [23, 24].

Fuzzy model and expert systems were developed to predict a gas condensate dewpoint pressure using gas composition and reservoir temperature [25, 26]. Different intelligent systems [27] were proposed such as GA-RBF, support vector machines (ML), fuzzy logic, genetic algorithms (GA), and an artificial neural network to estimate DPP.

Swarm optimization algorithm technique was established for accurate prediction of dewpoint pressure [28]. A new empirical K-value equation developed a new empirical K-value equation to compute the dew pressure using 81 gas condensate reservoir sample data from published literature [29]. Gene expression programming with multiple regression analysis were combined for estimating the DPP in gas condensate [30].

A novel correlation was proposed using computational intelligence algorithms, such as Support Vector Machines (SVM), and Functional Networks (FN), to determine the DPP for gas condensate reservoirs [31]. Adaptive neuro-fuzzy approach, hybrid soft computing approaches and hybrid intelligent approaches models were comprised for predicting DPP of gas condensate reservoirs [32-33]. 721 data points were used to develop artificial neural network (ANN) models with combining GA and PSO to predict DPP [34].

Different machine learning models and Multilayer Perceptron Neural Network developed for predicting DPP using 681 published data samples [34, 35]. From the above searches, we noticed that the uncertainty and complexity existent in the most gas reservoir correlations as well as several intelligent systems have applied to overcome these challenges. On the other hand, the application of the hybrid of these systems is still fewer.

Currently, the hybrid intelligent models were utilized in reservoir fluid properties calculation [36-38]. Hybrid models, such as those combining neural networks with optimization algorithms like PSO, further improve predictions for oil well output and energy [39-41]. The power of Hybrid models and AI lies in their ability to

investigate huge amounts of data, identify patterns, and make guesses or judgments based on that analysis [42, 43].

## 3- Data acquisition

In this study, the database was compiled from both literature sources and reported experimental data. A total of approximately 880 data samples were gathered to develop two hybrid models. This dataset comprises 579 measured data points obtained from different worldwide oil fields as PVT reports, and an additional 301 measured data points collected from literature [4-8]. Notably, this database is larger than those utilized in previously published studies.

The dataset was carefully screened for missing values and duplicate entries. Outliers were checked based on physical plausibility and statistical limits. All variables were normalized to improve numerical stability during model training. The dataset was randomly divided into 70% for training and 30% for testing to evaluate model generalization.

Table 1 depicts the ranges of all gas condensate parameters. The input of these data included temperature T, molecular weight heptane plus $MWC_{7+}$, specific gravity $SG_{C7+}$, and the composition of fluid ($C_1$-$C_6$, $C_{7+}$, and mole % of $CO_2$, $H_2S$, $N_2$) of model and the output is dew-point pressure (DPP). 70% and 30% of these simples were used to train and test the proposed models respectively. In additional, the database was normalized to avoid numerical difficulties during the computations. Statistical error analysis was used to check the performance and accuracy of those presented models.

**Table 1.** The ranges of gas condensate database

| Parameters | Min. | Max. |
|---|---|---|
| Dewpoint pressure, DPP | 890 | 9830 |
| Reservoir temperature, T | 46 | 339 |
| Molecular weight of heptane plus, $MW_{C7+}$ | 0 | 250 |
| Specific gravity of heptane plus, $SG_{C7+}$ | 0 | 0.8936 |
| Methane mole fraction, $C_1$ | 0.0349 | 0.967 |
| Ethane mole fraction, $C_2$ | 0.0037 | 0.608 |
| Propane mole fraction, $C_3$ | 0.0011 | 0.193 |
| Butane mole fraction, $C_4$ | 0.0017 | 0.371 |
| Pentane mole fraction, $C_5$ | 0 | 0.126 |
| Hexane mole fraction, $C_6$ | 0 | 0.099 |
| Heptane plus mole fraction, $C_{7+}$ | 0 | 0.156 |
| Hydrogen sulfide mole fraction, $H_2S$ | 0 | 0.577 |
| Carbon dioxide mole fraction, $CO_2$ | 0 | 0.918 |
| Nitrogen mole fraction, $N_2$ | 0 | 0.435 |

## 4- Methodology

In order to gather the necessary information for reservoir engineering analysis, simulation, and surface facility design, the nonlinear multiple regression (NLMR) approach, Particle Swarm Optimization (PSO), Particle Swarm Optimization with Neural Networks (PSONN), and statistical error analysis were utilized to calculate the dew-point pressure of gas condensate reservoirs as following:

### 4.1. Nonlinear multiple regression (NLMR) model

Nonlinear Multiple Regression (NLMR) is a statistical technique used to model the relationship between one dependent variable and multiple independent variables when this relationship is nonlinear. Unlike linear regression, where the relationship is represented as a linear function of the parameters, NLMR allows for more complex patterns [44].

Nonlinear Multiple Regression (NLMR) contains dependent Variable (Y) which is the outcome or response variable you aim to predict, independent Variables ($X_1$, $X_2$, ..., $X_k$) which are predictor variables that influence the dependent variable, and nonlinear Function that is defined by a mathematical function that is nonlinear. This can be polynomial, exponential, and logarithmic [44]. The development of a nonlinear multiple regression model typically involves the following steps:

Data collection, data exploration, model selection, parameter estimation, model evaluation, interpretation and inference, prediction and validation, and model refinement and validation. The proposed workflow for this study is presented in Fig. 1.

### 4.2. Particle swarm optimization (PSO)

PSO is a robust optimization algorithm established by (Eberhart and Kennedy, 1995) depends on the movement of swarms. PSO generates an initial population of birds (particles) of random velocities and positions. These particles are assessed using a statistical activation fit function. The optimal solutions are obtained by optimize the bird's movement. For more descriptions about PSO technique [44].

### 4.3. Particle swarm optimization with neural networks (PSONN)

Artificial Neural Networks (ANNs) excel at modeling nonlinear relationships but face challenges like slow convergence, entrapment in local minima, and difficulties in determining optimal hidden layers and neurons. Gradient-based training in ANNs, such as backpropagation, often converges slowly due to complex error surfaces and initial weight sensitivity [44]. These methods struggle with noncontinuous problems and frequently trap solutions in local minima, hindering global optimization.

For these reasons, the PSO algorithm is applied to avoid these difficulties by optimizing the weights of ANN model. The PSO algorithm is a robust searching which has the ability to avoid the local minimum point and fast convergence [45].

Particle Swarm Optimization (PSO) addresses these issues by optimizing ANN weights through population-based global search, enabling faster convergence and escape from local minima. PSO requires no gradient information, making it robust for nonlinear, high-dimensional problems common in petroleum engineering applications like reservoir prediction [46].

This combination is called PSONN model. The PSONN is combination models which run in two steps. In the first step, the PSO is applied to obtain the optimal weights of the networks. In the second step, the ANN model is then run for learning the rules and adjusts the last weights [46].

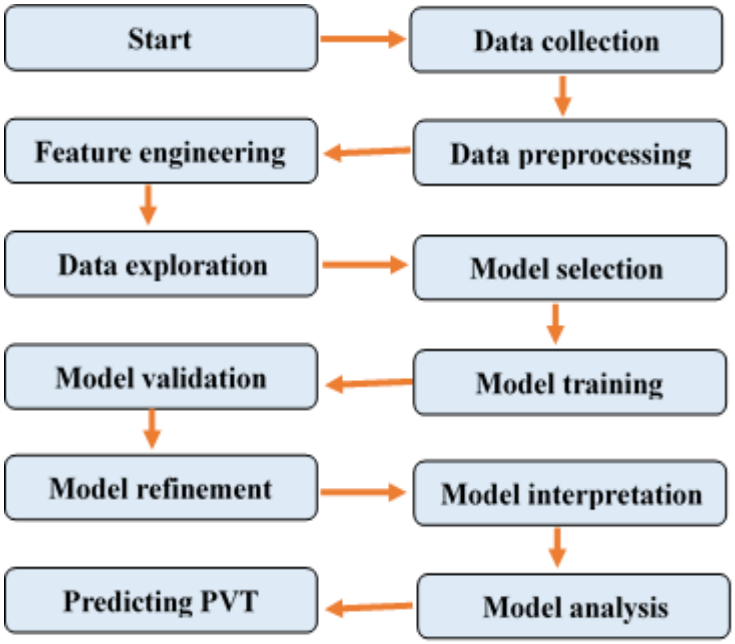


**Fig. 1.** The proposed workflow for this study

### 4.4. Statistical error analysis

The criteria used in this study were maximum/minimum absolute error, the root mean square error (RMSE), absolute percent relative error (APRE), and the correlation coefficient (CC) as shown in Table 2.

**Table 2.** Type of error analysis used in this study [6]

| Type of Error | Formula |
|---|---|
| Residual Error, ($E_i$) | $E_i = Y - Y_{pred}$ |
| Correlation Coefficient, (CC) | $CC = 1 - \frac{\sum_{i=1}^{n}(E_i)^2}{\sum_{i=1}^{n}(Y-\bar{Y})^2}$ |
| The Root Mean Square Error, (RMSE) | $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i)^2}$ |
| Absolute Percent Relative Error, (APRE) | $APRE = \frac{100}{n}\sum_{i=1}^{n}\frac{\lvert E_i \rvert}{Y}$ |

## 5- New approaches development

### 5.1. Development of new NLMR dew-point pressure correlation (NLMR DPP)

The New NLMR dew-point pressure (DPP) correlation is predicted as a direct function of temperature T, molecular weight heptane plus, specific gravity (SG), $C_{7+}$, and the composition of fluid ($C_1$-$C_6$, $C_{7+}$, and mole % of $CO_2$, $H_2S$, $N_2$) as Eq. 10. Nonlinear multiple regression analyses and Excel program exactly solver tool was used to generate the proposed dew-point pressure correlations. The predicted nonlinear regression DPP correlation is provided after evaluating several regression scenarios and

testing many possible combinations by using Nonlinear multiple regression and Excel program exactly solver tool as follows:

$$DDP = \left(\frac{A}{B}\right) + \left(\frac{D}{E}\right) \quad (10)$$

Where:

$$A = 14.37 - 4.87 * C_1 + 112.08 * C_2 - 0.00001 * C_4 + 70.7 * (C_4)^2 + 909.9 * C_5 - 21891 * C_6 + 353.8 * H_2S - 0.049 * (T + 460)$$

$$B = 0.0014 * (T + 460) + 0.1257$$

$$D = 6626.39 + 43.647 * C_1 * M_W\_5760.65 * C_3 - 23159.99 * C_{7+} + 1791.075 * \ln(C_{7+}) + 5078.48 * CO_2 + 7079.373 * N_2$$

$$E = (1.704 - SG)$$

5.2. Development of hybrid PSONN model

Neural Network (ANN) was developed with one hidden layer with 25 neurons. Then, PSO algorithm was used to adjust the weights and bias of the network values. Moreover, the ANN model was applied to train the network. Also, the number of dimensions in PSO technique is equal to number of weights of the network that depend on the network architecture and input data. Table 3 shows the best configuration of PSONN model.

**Table 3.** The best configuration of PSONN approach

| | |
|---|---|
| Max iteration | 200 |
| Number of particles | 200 |
| Dimension's | 376 |
| Inertia weight (w) | 0.8 |
| Maximum velocity, (v) | 3 |
| Cognitive parameter (c1) | 0.1 |
| Social parameter (c2) | 1 |

The dimensions of PSO algorithm were determined using the following Equation:

$$\text{Dimensions} = (\text{hidden} * \text{output hidden}) + (\text{input} * \text{hidden input}) + \text{hidden}_{\text{bias}} + \text{output}_{\text{bias}}$$

## 6- Results and discussions

In this study, nonlinear multiple regression (NLMR) approach and intelligent hybrid PSONN model were developed to determine the dew-point pressure for condensate gas. The NLMR and PSONN developed models were discussed in this section to calculate the dew-point pressure. The accuracy and performance of these models was compared with the common dew-point determination models presented in the literatures.

Fig. 2 depicts the best performance of the PSO technique for DPP. As observed from previous figure, the PSO is used to optimize parameters for DPP prediction. PSO generally aims to minimize errors by optimizing particle positions representing weights in models.

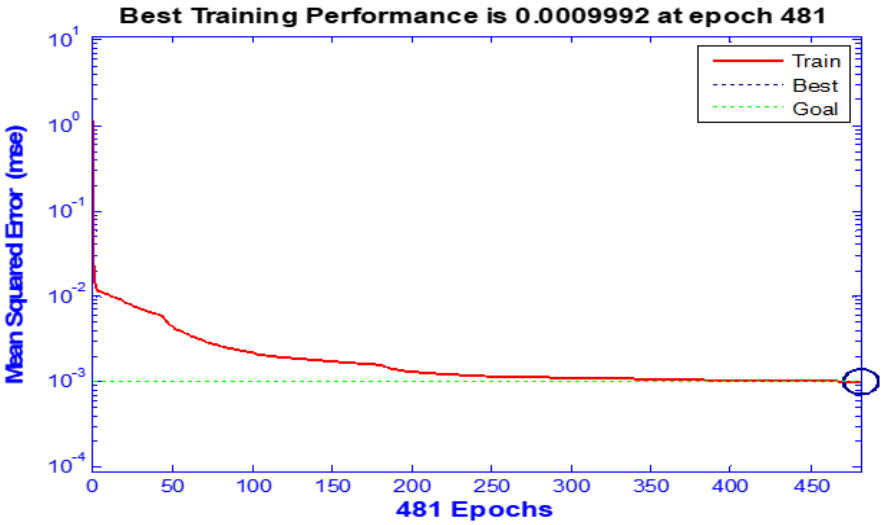


**Fig. 2.** The best performance of PSO technique

The best training performance of the PSONN model is showed in Fig. 3. The PSONN hybrid models demonstrate improved training performance where PSO optimizes initial weights, then a backpropagation algorithm refines the model in training to achieve low errors.

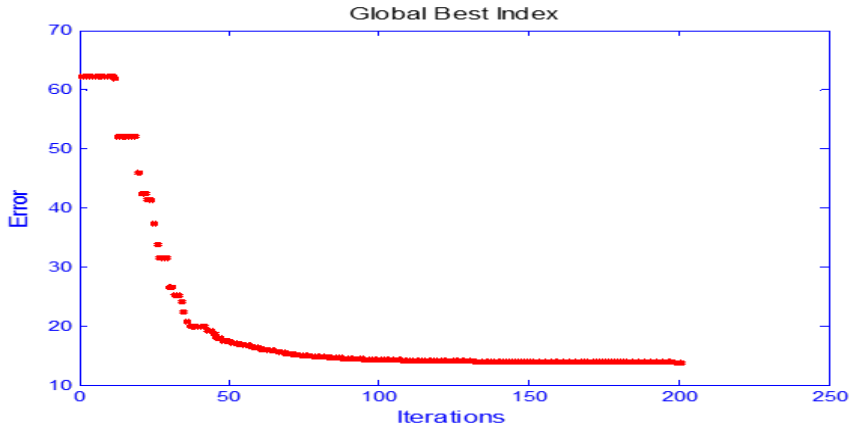


**Fig. 3.** The best training performance of the PSONN model

Fig. 4 illustrates the cross-plot between actual and predicted PSONN model. As concluded from the figure, the Cross-plots between actual and predicted DPP values help visually and statistically assess model accuracy. A well-performing model's points lie close to the 1:1 line, indicating predictions closely match actual values. The cross-plot between actual and the predicted NLMR model as shown in Fig. 5.

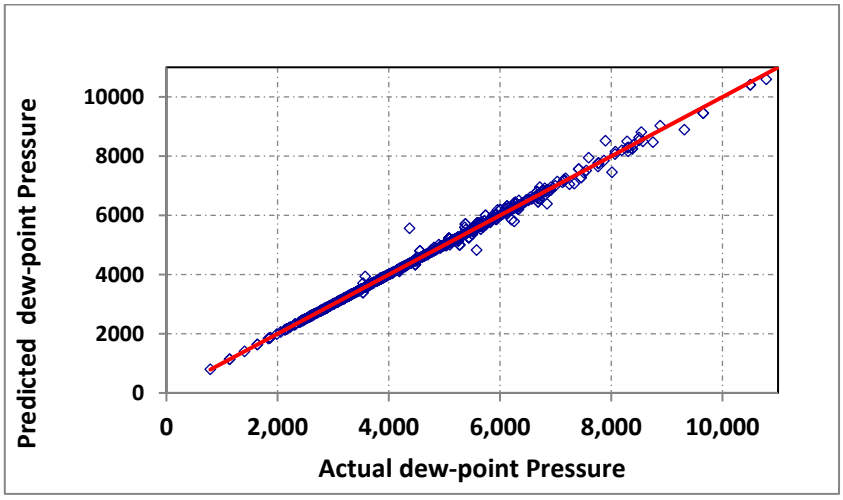


**Fig. 4.** The cross-plot of PSONN model

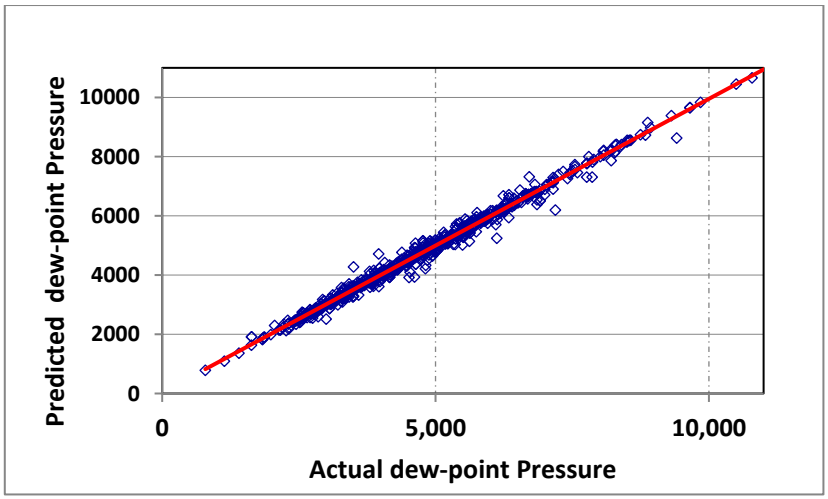


**Fig. 5.** The cross-plot of NLMR model

Similar to Fig. 4 but specifically for the nonlinear multiple regression (NLMR) model, demonstrating its predictive capability through predicted vs actual cross-plot. Fig. 6 shows the comparing the published AI models to proposed models for predicting DPP. Comparisons typically show that hybrid models like PSONN

correlations can outperform traditional AI models by achieving lower average absolute relative errors (AARE) and higher correlation coefficients (CC).

Fig. 7 displays the comparison of the AARE and CC for the developed NLMR DPP correlation in this study and the published DPP correlations. AARE measures average prediction errors relative to true values; lower is better. CC indicates the strength of correlation between predicted and actual values; higher is better. The developed NLMR correlation shows improved AARE and CC compared to published models, indicating better prediction accuracy and reliability.

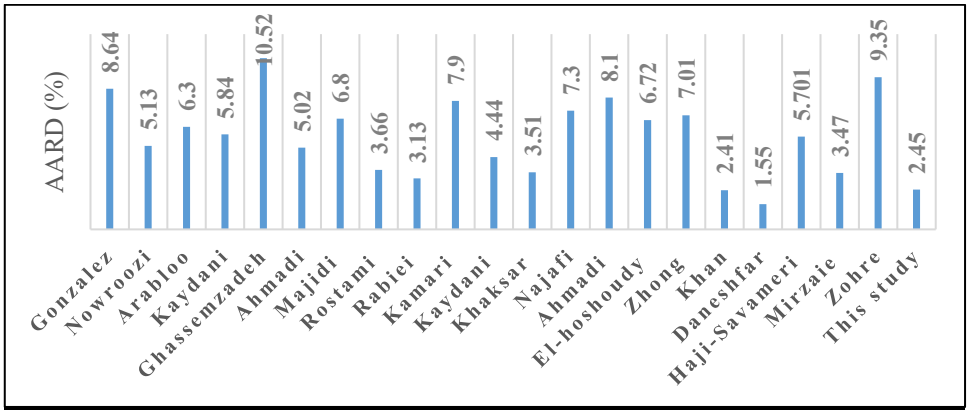


**Fig. 6.** Comparing the published AI models to proposed models for predicting DPP

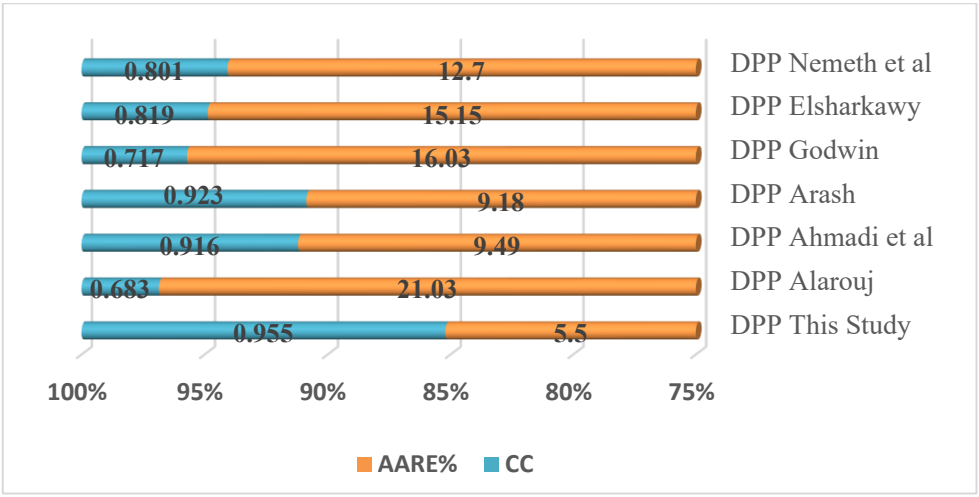


**Fig. 7.** Comparing of the AARE and CC for the developed NLMR DPP correlation in this study and the published DPP correlations

Table 4 described the error analysis results of PSONN model. The PSONN model achieved the APRE% (2.47) and the CC equal to 0.995. Table 5 displays the comparison between 24 published AI models and the proposed models for predicting dewpoint pressure according to the year of publication, models and methods utilized, number of data samples, and APRE (%). This table showed the different AI techniques such as GA-ANN, RBF, MLP, ANN, LSSVM, ANFIS, MGGP, and SVM by several authors and their used number of data samples.

The proposed models were compared with previously published correlations and AI models using reported performance statistical error analysis. While some studies achieved low errors using small datasets, the proposed PSONN model achieved competitive accuracy using a significantly larger and more diverse dataset, indicating stronger generalization capability as follows:

Khan models have achieved excellent APRE values with 2.41%; but they have just used fewer data samples comparing to other models. Rostami model obtained an excellent error of 3.660 % for relatively large data sets (562); however, there is not a respectable balance between the training APRE (%) values 1.997 and testing APRE (%) values 10.287% dataset's accuracy. Haji-Savameri and Mirzaie used different AI models with large (632 and 681) data samples and the best type of them achieved APRE equal to 5.701 and 3.4698 respectively. Although Gonzalez and Jaghdan used a larger dataset with 802 and789 data samples, they obtained quite high APRE equal to 8.64 and 9.35 respectively comparing to the errors of previous models.

In this study, the largest databases are used to develop the two hybrid models (NFuzzy and PSONN). The results displayed that the two developed hybrid models achieved a better accuracy compared with published AI models in the literatures for predicting of the DPP of condensate gas

as shown in Table 4. Table 5 showed a respectable balance between the training and testing APRE (%) values of NLMR and PSONN models. Table 4 and Table 5 also display the capability of the PSONN technique to estimate the DPP in more accurate than NLMR technique. This technique shows also the best model with the lowest APRE (2.45) and the highest CC (0.995).

**Table 4.** Comparing the published AI models to proposed models for predicting DPP

| Index | Year | Reference | Method | No. | AARD (%) |
|---|---|---|---|---|---|
| 1 | 2003 | Gonzalez[19] | MLP | 802 | 8.64 |
| 2 | 2009 | Nowroozi[24] | ANFIS | 110 | 5.13 |
| 4 | 2013 | Kaydani[22] | LM-MLP | 100 | 5.84 |
| 5 | 2013 | Ghassemzadeh[25] | ANFIS | 111 | 10.52 |
| 6 | 2014 | Ahmadi[16] | LSSVM | 404 | 5.02 |
| 8 | 2014 | Rostami [26] | GA-RBF | 562 | 3.66 |
| 9 | 2015 | Rabiei [23] | ANN | 308 | 3.1315 |
| 10 | 2016 | Kamari [15] | GEP | 562 | 7.9 |
| 11 | 2016 | Kaydani [22] | MGGP | 158 | 4.44 |
| 12 | 2016 | Manshad [28] | ANN-PSO | N.A. | 3.513 |
| 13 | 2016 | Najafi [27] | GA-RBF | 564 | 7.3 |
| 14 | 2017 | Ahmadi [17] | GEP | N.A. | 8.1 |
| 15 | 2018 | El-hoshoudy [30] | GEP | 480 | 6.72 |
| 16 | 2018 | Zhong [49] | PSO-MKF-SVM | 568 | 7.01 |
| 17 | 2019 | Khan [31] | ANN | 82 | 2.41 |
| 18 | 2020 | Ali [32] | ANFIS | 168 | N.A. |
| 20 | 2020 | Haji-Savameri [33] | MLP-BR | 632 | 5.701 |
| 21 | 2021 | Mirzaie [35] | AI | 681 | 3.4698 |
| 23 | 2022 | Han [36] | GA-ANN | 721 | N.A. |
| 24 | 2023 | Jaghdan [36] | DT | 789 | 9.35 |
| **25** | **2026** | **This study** | **PSONN** | **880** | **2.45** |

**Table 5.** Estimation errors for predicting the DPP using NLMR and PSONN models

| Database | NLMR Model | PSONN Model | Data Samples |
|---|---|---|---|
| | APRE% | APRE% | |
| **Training Data** | 5.50 | 2.45 | 612 |
| **Testing Data** | 5.55 | 2.48 | 268 |
| **All Data** | 5.57 | 2.47 | 880 |

## 7- Conclusions

The main conclusions of this study are as follows:

- This study developed and evaluated nonlinear regression and hybrid artificial intelligence models for predicting dew-point pressure in gas condensate reservoirs.
- The results displayed the PSONN models can outperform the NLMR model for both training and testing data.
- Among the previously AI models, the PSONN displayed the best performance with APRE (2.45 %) and CC (0.995) values for estimating dew-point pressure.
- The hybrid PSONN framework demonstrated superior accuracy and stability compared to the NLMR model and previously published correlations.
- The improved performance is attributed to the global optimization capability of PSO combined with nonlinear mapping of ANN.
- The PSONN technique can be merged in any program to improve the accuracy of dew-point pressure and should be taken in consideration into any production design calculation and gas reservoir characterization.
- Future research should investigate transfer learning strategies and model adaptability to evolving reservoir conditions.

## Abbreviations

| | |
|---|---|
| ANFIS | Adaptive-Neuro-Fuzzy Inference System. |
| ANN | Artificial Neural Network. |
| NLMR | Non-Linear Multiple Regression. |
| GEP | Gene Expression Programming. |
| CSA | Coupled Simulated Annealing. |
| DT | Decision Tree. |
| GA | Genetic Algorithm. |
| LM | Levenberg–Marquardt. |
| MGGP | Multi-Gene Genetic Programming |
| MKF | Mixed Kernels Function |
| ML | Machine Learning |
| MLP | Multi-layer perceptron |
| PSO | Particle swarm optimization |
| RBF | Radial basis function |
| SVM | Support-vector machines |

**List of symbols**

| | |
|---|---|
| APRE | Absolute Percent Relative Error. |
| $C_1$ | Methane mole fraction (Fraction). |
| $C_2$ | Ethane mole fraction |
| $C_3$ | Propane mole fraction. |
| $C_4$ | Butane mole fraction. |
| $C_5$ | Pentane mole fraction. |
| $C_6$ | Hexane mole fraction. |
| $C_{7+}$ | Heptane plus concentration. |
| $CO_2$ | Carbon dioxide mole fraction. |
| CC | Coefficient of determination. |
| DPP | Dew point pressure (psi). |
| $E_i$ | Residual Error |
| $H_2S$ | Hydrogen sulfide mole fraction. |
| $MWC_{7+}$ | Molecular weight of heptane plus (g/mol) |
| $N_2$ | Nitrogen mole fraction. |
| RMSE | Root mean squared error |
| SD | Standard deviation |
| $SGC_{7+}$ | Specific gravity of heptane plus (Fraction) |
| T | Temperature (°F) |
| Y | Actual Data |
| $Y_{pred}$ | Predicted Data |
| n | Number of data |

**Acknowledgements**

We, as authors, appreciate anonymous reviewers for their insightful comments to improve this work.

**Funding**

The authors received no financial support for the research and/or authorship of this article.

**Data availability**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

**References**

[1] M. Haji-Savameri, N. A. Menad, S. N. Apourvari, A. H. Sarapardeh, "Modeling dew point pressure of gas condensate reservoirs: Comparison of hybrid soft computing approaches, correlations, and thermodynamic models," *Journal of Petroleum Science and Engineering*, Volume 184, January 2020. https://doi.org/10.1016/j.petrol.2019.106558

[2] Z. E. Jaghdan, A. Tatar, A. Shokrollahi, J. Bon, A. Zeinijahromi," Machine learning modelling of dew point pressure in gas condensate reservoirs: application of decision tree-based models " *Neural Computing and Applications*, pp. 1973–1995, 2024. https://doi.org/10.1007/s00521-023-09201-9

[3] P. Ikpeka1, J. Ugwu1, P.l Russell, G. Pillai, " Performance Evaluation of Machine Learning Algorithms in Predicting Dew Point Pressure of Gas Condensate Reservoirs," *Discover Applied Sciences*, 2020. https://doi.org/10.1007/s42452-020-03811-x

[4] A. N El-hoshoudy, S. Gomaa, S.M. Desouky "Prediction of Dew Point Pressure in Gas Condensate Reservoirs Based on a Combination of Gene Expression Programming (GEP) and Multiple Regression Analysis." *Petroleum Petrochemical Engineering Journal*, Medwin Publishers, 2018. https://doi.org/10.23880/PPEJ-16000163

[5] S. O. Baarimah and A. O. Baarimah, "PVT Properties for Yemeni Reservoirs Using an Intelligent Approach," *3rd International Sustainability and Resilience Conference,* 2021. https://doi.org/10.1109/IEEECONF53624.2021.9668185

[6] A. Al-Gathe, S. O. Baarimah, A. M. Al-Khudafi, M. Bawahab, and H. Dmour, "Hybrid approach for gas viscosity in Yemeni oil fields," *Earth Science Informatics [ESIN]*, vol. 17, no. 1, pp. 475–482, Feb. 2024. https://doi.org/10.1007/s12145-023-01121-5

[7] S. O. Baarimah, N. M. Al-Aidroos, and K. S. Ba-Jaalah, "Using Chemical Composition of Crude Oil and Artificial Intelligence Techniques to Predict the Reservoir Fluid Properties," in *First International Conference of Intelligent Computing and Engineering (ICOICE),* 2019, pp. 1–5. https://doi.org/10.1109/ICOICE48418.2019.9035135

[8] A. Al-Gathe, K. A. A., Fattah, A., El-Banbi, and K. El-Metwally, "A Hybrid Neuro-Fuzzy Approach for Black Oil Viscosity Prediction," *International Journal of Innovation and Applied Studies*, 13(4), 2015.

[9] A. L. K. Nemeth and H. T. Kennedy, "A Correlation of Dewpoint Pressure with Fluid Composition and Temperature," *Society of Petroleum Engineers Journal*, vol. 7, no. 02, pp. 99–104, Jun. 1967. https://doi.org/10.2118/1477-PA

[10] A. A. Humoud and M. A. Al-Marhoun, "A New Correlation for Gas-condensate Dewpoint Pressure Prediction," *Proceedings of the Middle East Oil Show*, pp. 877–884, Mar. 2001. https://doi.org/10.2118/68230-MS

[11] A. M. Elsharkawy, "Predicting the dew point pressure for gas condensate reservoirs: empirical models and equations of state," *Fluid Phase Equilibria*, vol. 193, no. 1–2, pp. 147–165, Jan. 2002. https://doi.org/10.1016/S0378-3812(01)00724-5

[12] Il. Marruffo, J. Maita, J. Him, and G. Rojas, "Correlations to Determine Retrograde Dew Pressure and C7+ Percentage of Gas Condensate Reservoirs on basis of Production Test Data of Eastern Venezuelan Fields," *SPE Proceedings - Gas Technology Symposium*, pp. 481–486, Apr. 2002. https://doi.org/10.2118/75686-MS

[13] E. M. E. M. Shokir, "Dewpoint Pressure Model for Gas Condensate Reservoirs Based on Genetic Programming," *Paper presented at the CIPC/SPE Gas Technology Symposium 2008 Joint Conference, Calgary, Alberta, Canada,* June 2008. https://doi.org/10.2118/114454-MS

[14] O. N. Godwin, "A New Analytical Method for Predicting Dew Point Pressures for Gas Condensate Reservoirs," *Society of Petroleum Engineers - 36th Nigeria Annual Int. Conf. and Exhibition 2012, NAICE 2012 - Future of Oil and Gas: Right Balance with the Environment and Sustainable Stakeholders' Participation*, vol. 2, pp. 847–857, Aug. 2012. https://doi.org/10.2118/162985-MS

[15] A. Kamari, M. Sattari, A. H. Mohammadi, and D. Ramjugernath, "Rapid method for the estimation of dew point pressures in gas condensate reservoirs," *Journal of the Taiwan Institute of Chemical Engineers*, vol. 60, pp. 258–266, Mar. 2016. https://doi.org/10.1016/J.JTICE.2015.10.011

[16] M. A. Ahmadi and M. Ebadi, "Evolving smart approach for determination dew point pressure through condensate gas reservoirs," *Fuel*, vol. 117, no. PARTB, pp. 1074–1084, Jan. 2014. https://doi.org/10.1016/J.FUEL.2013.10.010

[17] M. A. Ahmadi and A. Elsharkawy, "Robust correlation to predict dew point pressure of gas condensate reservoirs," *Petroleum*, vol. 3, no. 3, pp. 340–347, Sep. 2017. https://doi.org/10.1016/J.PETLM.2016.05.001

[18] M. Alarouj, O. Alomair, and A. Elsharkawy, "Gas condensate reservoirs: Characterization and calculation of dew-point pressure," *Petroleum Exploration and Development*, vol. 47, no. 5, pp. 1091–1102, Oct. 2020. https://doi.org/10.1016/S1876-3804(20)60120-3

[19] A. González, M. A. Barrufet, and R. Startzman, "Improved neural-network model predicts dewpoint pressure of retrograde gases," *Journal of Petroleum Science and Engineering*, vol. 37, no. 3–4, pp. 183–194, Mar. 2003. https://doi.org/10.1016/S0920-4105(02)00352-2

[20] M. K. Akbari, F. J. Farahani, and Y. Abdy, "Dewpoint Pressure Estimation of Gas Condensate Reservoirs, Using Artificial Neural Network (ANN)," *69th European Association of Geoscientists and Engineers Conference and Exhibition 2007: Incorporating SPE EUROPEC 2007*, vol. 6, pp. 3422–3432, Jun. 2007, https://doi.org/10.2118/107032-MS

[21] M. Al-Dhamen and M. Al-Marhoun, "New Correlations for Dew-Point Pressure for Gas Condensate," *Society of Petroleum Engineers - Saudi Arabia Section Young Professionals Technical Symposium 2011*, pp. 1–18, Mar. 2011. https://doi.org/10.2118/155410-MS

[22] H. Kaydani, A. Hagizadeh, and A. Mohebbi, "A Dew Point Pressure Model for Gas Condensate Reservoirs Based on an Artificial Neural Network," *Petroleum Science and Technology*, vol. 31, no. 12, pp. 1228–1237, Jun. 2013. https://doi.org/10.1080/10916466.2010.540616

[23] A. Rabiei, H. Sayyad, M. Riazi, and A. Hashemi, "Determination of dew point pressure in gas condensate reservoirs based on a hybrid neural genetic algorithm," *Fluid Phase Equilibria*, vol. 387, pp. 38–49, Feb. 2015. https://doi.org/10.1016/J.FLUID.2014.11.027

[24] S. Nowroozi, M. Ranjbar, H. Hashemi, and M. Schaffie, "Development of a neural fuzzy system for advanced prediction of dew point pressure in gas condensate reservoirs," *Fuel Processing Technology*, vol. 90, no. 3, pp. 452–457, Mar. 2009. https://doi.org/10.1016/J.FUPROC.2008.11.009

[25] S. Ghassemzadeh, M. Shafflie, A. Sarrafi, and M. Ranjbar, "The Importance of Normalization in Predicting Dew Point Pressure by ANFIS," *Petroleum Science and Technology*, vol. 31, no. 10, pp. 1040–1047, May 2013. https://doi.org/10.1080/10916466.2011.598895

[26] H. Rostami-Hosseinkhani, F. Esmaeilzadeh, and D. Mowla, "Application of expert systems for accurate determination of dew-point pressure of gas condensate reservoirs," *Journal of Natural Gas Science and Engineering*, vol. 18, pp. 296–303, May 2014. https://doi.org/10.1016/J.JNGSE.2014.02.009

[27] A. Najafi-Marghmaleki, A. Tatar, A. Barati-Harooni, M. J. Choobineh, and A. H. Mohammadi, "GA-RBF model for prediction of dew point pressure in gas condensate reservoirs," *Journal of Molecular Liquids*, vol. 223, pp. 979–986, Nov. 2016. https://doi.org/10.1016/J.MOLLIQ.2016.08.087

[28] A. K. Manshad, H. Rostami, S. M. Hosseini, and H. Rezaei, "Application of artificial neural network particle swarm optimization algorithm for prediction of gas condensate dew point pressure and comparison with Gaussian processes regression particle swarm optimization algorithm," *Journal of Energy Resources Technology, Transactions of the ASME*, vol. 138, no. 3, May 2016. https://doi.org/10.1115/1.4032226

[29] S. Aghamiri, M. Tamtaji, and M. J. Ghafoori, "Developing a K-value equation for predict dew point pressure of gas condensate reservoirs at high pressure," *Petroleum*, vol. 4, no. 4, pp. 437–443, Dec. 2018. https://doi.org/10.1016/J.PETLM.2017.08.002

[30] El-hoshoudy AN, Gomaa S, and Desouky SM, "Prediction of Dew Point Pressure in Gas Condensate Reservoirs Based on a Combination of Gene Expression Programming (GEP) and Multiple Regression Analysis," *Petroleum & Petrochemical Engineering Journal,* 2018.

[31] M. R. Khan, S. Kalam, Z. Tariq, and A. Abdulraheem, "A Novel Empirical Correlation to Predict the Dew Point Pressure using Intelligent Algorithms," *Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2019, ADIP 2019*, Nov. 2019. https://doi.org/10.2118/197951-MS

[32] A. Ali and L. Guo, "Adaptive neuro-fuzzy approach for prediction of dewpoint pressure for gas condensate reservoirs," *Petroleum Science and Technology*, vol. 38, no. 9, pp. 673–681, May 2020. https://doi.org/10.1080/10916466.2020.1769655

[33] M. Haji-Savameri, N. A. Menad, S. Norouzi-Apourvari, and A. Hemmati-Sarapardeh, "Modeling dew point pressure of gas condensate reservoirs: Comparison of hybrid soft computing approaches, correlations, and thermodynamic models," *Journal of Petroleum Science and Engineering*, vol. 184, p. 106558, Jan. 2020. https://doi.org/10.1016/J.PETROL.2019.106558

[34] L. Han and S. Sarvazizi, "Applying Optimized ANN Models to Estimate Dew Point Pressure of Gas Condensates," *International Journal of Chemical Engineering*, vol. 2022, 2022. https://doi.org/10.1155/2022/1929350

[35] M. Mirzaie, H. Esfandyari, and A. Tatar, "Dew point pressure of gas condensates, modeling and a comprehensive review on literature data," *Journal of Petroleum Science and Engineering*, vol. 211, p. 110072, Apr. 2022. https://doi.org/10.1016/J.PETROL.2021.110072

[36] Z. E. Jaghdan, A. Tatar, A. Shokrollahi, J. Bon, and A. Zeinijahromi, "Machine learning modelling of dew point pressure in gas condensate reservoirs: application of decision tree-based models," *Neural Computing and Applications*, vol. 36, no. 4, pp. 1973–1995, Feb. 2024. https://doi.org/10.1007/s00521-023-09201-9

[37] A. Embaireeg, "A Reliable Multilayer Perceptron Neural Network Estimator of Gas Condensate Reservoir Initial Composition and Dew Point Pressure," *Society of Petroleum Engineers - ADIPEC, ADIP 2023*, Oct. 2023. https://doi.org/10.2118/216467-MS

[38] S. O. Baarimah, A. A. Al-Gathe, and A. O. Baarimah, "Modeling Yemeni Crude Oil Reservoir Fluid Properties Using Different Fuzzy Methods," *2022 International Conference on Data Analytics for Business and Industry, ICDABI 2022*, pp. 761–765, 2022. https://doi.org/10.1109/ICDABI56818.2022.10041519

[39] S. O. Baarimah, A. G. Abdelrigeeb, and A. B. Binmerdhah, "Predict Reservoir Fluid Properties of Yemeni Crude Oils Using Fuzzy Logic Technique," *2019 1st International Conference of Intelligent Computing and Engineering: Toward Intelligent Solutions for Developing and Empowering our Societies, ICOICE 2019*, Dec. 2019, https://doi.org/10.1109/ICOICE48418.2019.9035131

[40] S. O. Baarimah, A. O. Baarimah, W. S. Alaloul, M. A. Bazel, F. Mohammed and M. Bawahab, "A Bibliometric Analysis on the Applications of Artificial Intelligence in Petroleum Engineering," *4th International Conference on Data Analytics for Business and Industry (ICDABI)*, Bahrain, 2023, pp. 152-159, https://doi.org/10.1109/ICDABI60145.2023

[41] GM. Hamada, A. A. Al-Gathe, and A. M. Al-Khudafi, "Hybrid Artificial Intelligent Approach for Determination of Water Saturation using Archies Formula in Carbonate Reservoirs," *Journal of Petroleum & Environmental Biotechnology*, vol. 6, no. 6, pp. 1–7, 2015. https://doi.org/10.4172/2157-7463.1000250

[42] A. A. Al-Gathe, S. O. Baarimah, and A. M. Al-Khudafi, "Modelling gas compressibility factor using different fuzzy methods," in *AIP Conference Proceedings*, AIP Publishing LLC, 2022, p. 30031.

[43] A.-G. Abedelrigeeb, A. El-Banbi, A. Fattah, A. Kh., and K. A. El-Metwally, "An Artificial Intelligent Approach for Black Oil PVT Properties," *Journal of Physics: Conference Series*, 2021. https://doi.org/10.1088/1742-6596/1962/1/012026

[44] The MathWorks, Inc.

[45] J.R. Zhang, J. Zhang, T.M. Lok, M. R. Lyu, "A hybrid particle swarm optimization–back-propagation algorithm for feedforward neural network training", *Applied Mathematics and Computation*, Volume 185, Issue 2, pp. 1026-1037, 2007. https://doi.org/10.1016/j.amc.2006.07.025

[46] F. E. Junior, and G. G. Yen, " Particle swarm optimization of deep neural networks architectures for image classification, " *Swarm and Evolutionary Computation*, Volume 49, pp. 62-74, 2019. https://doi.org/10.1016/j.swevo.2019.05.010

# نماذج الشبكة العصبية الهجينة القائمة على سرب الجسيمات ونماذج الانحدار للتنبؤ بضغط نقطة الندى

**سالم عبيد باعارمه [١]، غريب مصطفى حماده [٢،*]، عبدالرقيب علي القاضي [١]، خالد سعيد باجعاله [١]**

*١ قسم هندسه البترول، جامعه حضرموت، المكلا، اليمن*
*٢ قسم هندسه البترول والغاز، الأكاديميه العربيه للعلوم والتكنولوجيا والنقل البحرى، الأسكندريه، مصر*

## الخلاصة

يُعدّ التنبؤ الدقيق بضغط نقطة الندى (DPP) أمرًا بالغ الأهمية لتطوير وإدارة إنتاج مكامن الغاز المكثف؛ إلا أن العلاقات التجريبية الحالية ونماذج التعلم الآلي المستقلة غالبًا ما تعاني من محدودية التعميم والحساسية لتغيرات البيانات. تتناول هذه الدراسة هذه الفجوة من خلال تطوير ومقارنة علاقة انحدار متعدد غير خطي (NLMR) و نموذج شبكة عصبية هجين مُحسَّن بخوارزمية سرب الجسيمات (PSONN) باستخدام مجموعة بيانات كبيرة ومتنوعة تضم ٨٨٠ عينة تجريبية جُمعت من الدراسات المنشورة ومكامن الشرق الأوسط. تم اختيار نموذج PSONN لقدرته على التغلب على قيود الشبكات العصبية، مثل بطء التقارب، من خلال تحسين أوزان الشبكة باستخدام ذكاء السرب العالمي. حقق نموذج PSONN الهجين دقة تنبؤية فائقة بنسبة خطأ نسبي متوسط (APRE) بلغت ٢.٤٥٪ ومعامل ارتباط (CC) بلغ ٠.٩٩٧، متفوقًا بذلك على كل من علاقة NLMR المقترحة والنماذج المنشورة سابقًا. تُظهر النتائج أن الإطار الهجين المُطور يُمكنه تحسين تقدير ضغط نقطة الندى بشكل كبير، مما يدعم توصيف الخزانات بشكل موثوق، وتصميم المنشآت السطحية، وتخطيط الإنتاج في حقول الغاز المكثف.

**الكلمات الدالة:** هجين، شبكة عصبية، سرب الجسيمات، انحدار غير خطي، ضغط نقطة الندى.