# An Optimized Hybrid Intelligent System for High-Accuracy Dewpoint Pressure Estimation

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*Abstract*— Dewpoint pressure (DPP) is a critical property of gas condensate reservoir development. Accurately estimating this property remains a significant challenge. Existing empirical correlations and iterative methods lack sufficient accuracy due to complexity and computational intensity. However, despite their utilization involving complex computations, they have not achieved sufficient accuracy. Several individual intelligent systems have been utilized to predict this property with good accuracy, but the application of hybrid models is less common. Therefore, this study proposes two hybrid intelligent models—Particle Swarm Optimization combined with Neural Networks (PSONN) and Neuro-Fuzzy (NFuzzy)—to enhance prediction accuracy of dewpoint pressure. Approximately 860 collected data points were used to develop these hybrid models. Inputs such as temperature (T), hydrocarbon composition, specific gravity, and molecular weight of heptane plus were utilized to predict the dewpoint pressure. In this study, the performance of both intelligent hybrid systems is compared to the most widely published Artificial Intelligence (AI) models. Based on statistical error analysis results, the new hybrid models outperform the published models. The results confirm that the PSONN hybrid model achieved the best performance with an absolute percent relative error (APRE) of 2.47%.

**Keywords—** *Artificial intelligence; Hybrid models; Neuro-Fuzzy; PSONN, Dewpoint Pressure*

## I. INTRODUCTION

If the wellbore pressure falls below the dewpoint pressure, the productivity of gas condensate reservoirs decreases rapidly. One simulation model is employed to study this phenomenon, revealing the formation of liquid condensate around the wellbore. The saturation of this liquid gradually increases, leading to a rapid reduction in the gas's effective permeability. Consequently, well productivity experiences a sharp decline [18].

The dewpoint pressure (DPP) is a key property for identifying gas condensate reservoirs. Therefore, accurate determination of the dewpoint pressure in gas condensate reservoirs is essential. A variety of methods have been introduced for calculating DPP in gas condensate reservoirs, including intelligent systems, graphical methods [49], different correlations, and even EOS-based approaches. Dewpoint pressure can be predicted using empirical correlations developed from experimental measurements [21]. Additionally, although equations of state can be employed for predicting dewpoint pressure, they have been reported to exhibit weak performance [46,47]. Devised an empirical correlation for calculating DPP. The impact of $H_2S$ on DPP was investigated by [15], discovering that the volume of liquid decreased with increasing $H_2S$ content using an empirical correlation. To develop an empirical correlation for DPP [24], collected gas-condensate data from western China. An empirical correlation for estimating DPP using data from gas-condensate reservoirs in the Middle East was devised [34]. Study [43] proposed a new empirical model specifically designed for estimating the dewpoint pressure. A new correlation for estimating DPP in gas condensates was introduced, and it was compared with existing correlations using 259 data sets [27]. Using 667 data samples [12] proposed a model based on multiple linear regressions. Although empirical correlations are commonly used for DPP prediction, their accuracy is limited due to dataset specificity and dependence on labor-intensive, costly experimental data. Consequently, various artificial intelligence techniques have been explored for dewpoint pressure prediction [53].

In petroleum engineering, the use of potent forecasting tools like artificial intelligence (AI) and machine learning (ML) models has been steadily increasing since 2003.

An Artificial Neural Network (NN) model was developed [28] to predict the dewpoint pressure of condensate gas reservoirs using 802 data samples. Various ANN models for predicting DPP were proposed based on 111 data sets [5]. An ANN technique sourced from Middle East reservoirs was developed using 113 data points, which yielded the best results [6]. Additionally, ANN introduced models for predicting DPP [37, 38, 50].

To predict the dewpoint pressure of gas condensate [25, 48], they developed a fuzzy model. using gas composition and reservoir temperature. Various intelligent systems, including support vector machines, fuzzy logic, genetic algorithms, and artificial neural networks, were proposed to estimate DPP [3]. The GA-RBF technique for accurately predicting dewpoint pressure was established [45, 51]. The ANN-PSO model to estimate DPP was utilized [42].A genetic programming model employed for DPP estimation [4, 36]. A novel empirical equation for estimating the K-value and calculating dew point pressure was formulated based on data from 81 gas condensate reservoir samples reported in prior studies [2].

Meanwhile, [19] utilized a hybrid modeling approach by integrating gene expression programming with multiple regression techniques for predicting dew point pressure in gas condensate systems.

Numerous studies have introduced intelligent computational methods to estimate dew point pressure in gas condensate reservoirs. For instance, SVM, ANN, and Functional Networks (FN) were implemented in a novel predictive framework [39]. A fuzzy logic-based estimation model was presented in [10], while [30] combined thermodynamic principles with hybrid intelligent systems to enhance prediction accuracy. In another effort, [32] utilized a dataset of 721 samples to develop ANN-based models, incorporating optimization algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). Similarly, [13] employed a least squares support vector approach tailored to various condensate gas systems. Machine learning techniques also featured prominently in [41], which focused on advanced DPP forecasting models. The Multilayer Perceptron (MLP) model proposed by [16], built on 80 data points, demonstrated high precision with an AARD of just 1.553%. Additional models were constructed using 681 publicly available samples by researchers in [23, 29, 33, 40, 44], and [22] applied ANN to a dataset of 141 entries to estimate dew point pressure effectively.

From the above searches, many iterative methods or empirical correlations have been utilized to predict DPP. However, these correlations are more complex, including a large number of factors, which require longer and more complicated calculations. In addition, the precision of these correlations has become inadequate for optimal estimations due to their limitations [20]. Thus, hybrid intelligent systems are employed to overcome these challenges as well, and these hybrid models are rarely applied in this field, and that is why we do our research.

Fluid properties (e.g., viscosity, bubble point pressure, and formation volume factor) have been effectively calculated using hybrid intelligence models, such as Particle Swarm Optimization Neural Networks (PSONN) and Neuro-Fuzzy (NFuzzy) systems.

For instance, [26, 31] utilized a PSONN-based approach, while [14] employed an NFuzzy model. Similarly, [7-9] demonstrated the effectiveness of combining PSONN and NFuzzy methods in this domain.

The objective of this work is to develop a robust model for accurate dewpoint pressure estimation. To achieve this, two hybrid models, NFuzzy and PSONN, were developed to enhance DPP estimation beyond existing approaches.

## II. Methods and Procedures

### A. *Particle swarm optimization)*

PSO is an optimization algorithm based on swarm movement developed by [17]. The PSO algorithm generates a swarm of particles with random positions and speeds in the search space. A statistical activation fit function is used to assess these particles by [52].The optimal solutions are obtained by optimizing the birds' movement.

The following steps describe how the PSO algorithm runs:

1. The PSO algorithm starts by dispersing a collection of particles throughout the solution area at random.
2. These particles move through the space with certain velocities, iteratively attempting to converge toward the optimal global position, referred to as *gbest*.
3. Each particle modifies its velocity in each iteration within the N-dimensional problem space according to three factors: the swarm's globally best location (gbest), its individual best-known position (pbest), and its previous velocity.
4. The fundamental principle of PSO involves guiding each particle to accelerate toward both its own best location and the swarm's best-known position, using randomly scaled influence factors at each step.

**Fig. 1** depicts the particle flying model. For more detailed descriptions of the PSO technique, refer to [1,17].

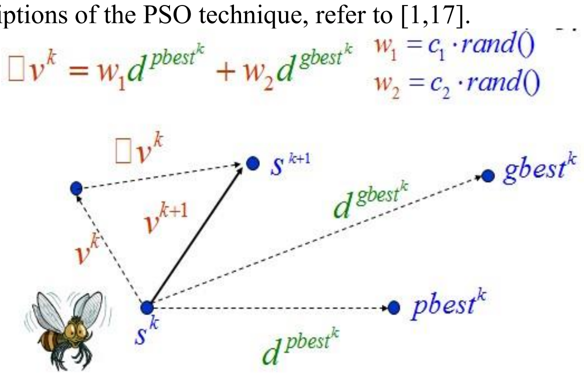


Fig.1 shows particle flying model

### B. *Development of PSONN model*

While Artificial Neural Networks (ANNs) exhibit high accuracy in handling nonlinear problems, they also possess several weaknesses. These include difficulties in figuring out the right number of hidden layers and neurons, delayed convergence, and a propensity to become stuck in local minimum points. The particle swarm optimization approach is frequently used to optimize the ANN model's weights in order to overcome these problems. PSO is renowned for its strong search skills, which allow it to quickly converge and avoid local minimum spots.

Combining the PSO algorithm with the ANN model is essential for achieving faster convergence and higher accuracy. Moreover, this combination can help overcome the weaknesses inherent in both algorithms. This combined model is referred to as the PSONN model. The PSO algorithm rapidly achieves convergence during the initial stages of a global search, whereas around the global optimum, the search process will become very slow. Consequently, integrating NN and PSO can reach faster convergent speed around the global optimum and increase the convergent accuracy at the same time.

The PSONN model operates in two steps. In the first step, PSO is applied to obtain the optimal weights of the networks. In the second step, the ANN model is then utilized to learn the rules and further adjust the weights. Fig. 2 illustrates the learning process steps of the PSONN. First, the neural network initializes its weights and biases as random particles positioned within the problem space. The dimensions of this space correspond to the number of weights and thresholds requiring optimization. Next, the process applies a BP algorithm to the initial connection weights and thresholds established by the PSO. Finally, for each particle, the system calculates its velocity and updates its position. Then, the PSO algorithm adjusts the NN parameters, and the adopted feedforward neural network has one hidden layer. The optimal first hidden layer uses tansig as a transfer function, whereas the other output transfer function is purelin.

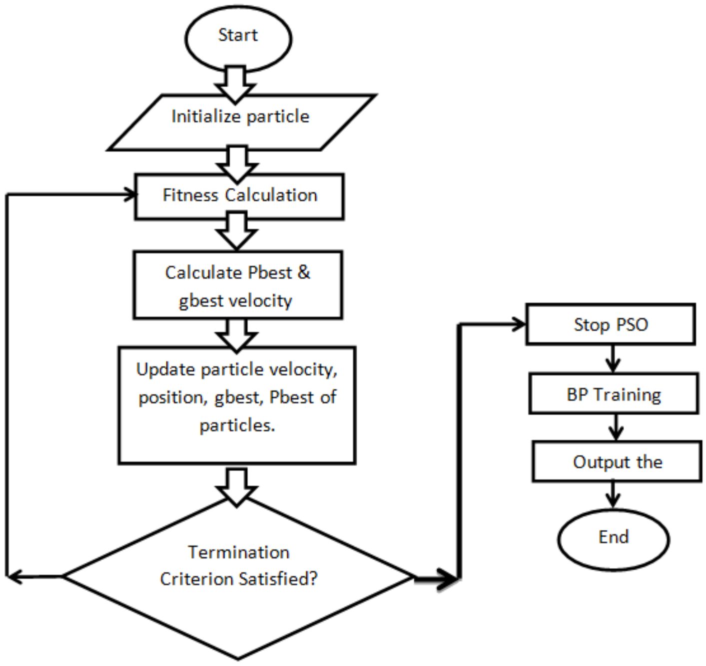


Fig. 2 The fundamental process of PSO.

*C. Development of NFuzzy model*

The NFuzzy model is the same as the Adaptive Neuro-Fuzzy Inference System (ANFIS) in this study. The NFuzzy model uses conditional functions to select target parameters by combining fuzzy logic and artificial neural networks.

This hybrid model combines fuzzy and ANN techniques during the training stage to enhance learning capabilities, as described by [35].

In general, the NFuzzy model utilizes Subtractive Clustering type functions, specifically genfis2, to estimate dewpoint pressure. Additionally, the final configuration of the NFuzzy model can be adjusted to minimize computational errors.

## III. DATA ACQUISITION

A comprehensive database of approximately 860 samples compiled from literature and experimental studies was used. This dataset includes 579 measured data points obtained from a thesis [46, 47], another 254 measured data points collected from the Middle East field, and 27 data points extracted from literature, as documented by [19]. Notably, this database is larger than those used in previous studies.

To ensure data integrity, the collected samples underwent thorough preprocessing steps. These steps involved checking for data consistency, identifying and removing duplicate entries, and addressing any missing values. This meticulous data preparation process was crucial for minimizing uncertainties in subsequent computations, as emphasized by [44].

Table 1 depicts the ranges of all gas condensate parameters. The input of these data includes the temperature, molecular weight, and specific gravity of heptane plus (C7+), and the fluid composition (C1–C7+, CO2, H2S, N2) of the model, and the output is dewpoint pressure. Data were split 70% for training and 30% for testing.

In additional, the database was normalized to avoid numerical difficulties during the computations. The total data is scaled among 0 and 1 by the following formula:

$$NX = \frac{(\mathrm{Input} - \mathrm{Input}_{\mathrm{min}})}{(\mathrm{Input}_{\mathrm{max}} - \mathrm{Input}_{\mathrm{min}})} \quad (1)$$

Where NX is the normalized output data, $\mathrm{Input}_{\mathrm{max}}$ , $\mathrm{Input}_{\mathrm{min}}$ , are the maximum and minimum of data respectively and Input is the original data. Statistical error analysis was used to check the performance and accuracy of those presented models.

TABLE 1. DEPICTS THE RANGES OF GAS CONDENSATE DATABASE

| Parameters | Min. | Max. | Mean |
|---|---|---|---|
| Dewpoint pressure, psi | 790 | 11830 | 4597.7 |
| Reservoir temperature, oF | 40 | 337 | 202.83 |
| Molecular weight C7+, MWC7+ | 0 | 253 | 146.02 |
| Specific gravity C7+, SGC7+ | 0 | 0.89342 | 0.777 |
| Methane, C1 | 0.0349 | 0.9668 | 0.804 |
| Ethane, C2 | 0.0037 | 0.604 | 0.059 |
| Propane, C3 | 0.0011 | 0.19 | 0.030 |
| Butane, C4 | 0.0017 | 0.375 | 0.023 |
| Pentane, C5 | 0 | 0.123 | 0.012 |
| Hexane, C6 | 0 | 0.0977 | 0.010 |
| Heptane plus, C7+ | 0 | 0.153 | 0.035 |
| Hydrogen Sulfide, H2S | 0 | 0.579 | 0.007 |
| Carbon dioxide, CO2 | 0 | 0.9192 | 0.017 |
| Nitrogen, N2 | 0 | 0.4322 | 0.009 |

The models' performance was assessed using statistical metrics including Absolute Percent Relative Error (APRE), Root Mean Squared Error (RMSE), standard deviation, and correlation coefficient (CC), as shown in Table II.

TABLE 2. TYPE OF ERROR ANALYSIS USED IN THIS STUDY

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

## IV. RESULTS AND DISCUSSION

Two hybrid models of intelligent systems were created for this study in order to calculate dewpoint pressure. This section discusses the NFuzzy and PSONN models developed for calculating the dewpoint pressure. Furthermore, the accuracy and performance of these models were compared with commonly used dewpoint determination models presented in the literature.

### *A. Hybrid PSONN Model*

An ANN was constructed with a single hidden layer comprising 25 neurons. Subsequently, the PSO algorithm was employed to adjust the weights and biases of the network. Additionally, the ANN model was utilized to train the network. The number of dimensions in the PSO technique corresponds to the number of weights of the network, which is contingent upon the network architecture and input data. The optimal configuration of the PSONN model is presented in Table 3.

TABLE 3. SHOWS THE OPTIMAL PSONN METHOD CONFIGURATION.

| | |
|---|---|
| Maximum 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 Equation (2).

$$X = (H \cdot HO) + (I \cdot HI) + H_{bias} + O_{bias} \quad (2)$$

Following adjustments to the ANN model's weights and biases, Fig. 3 displays the PSO technique's performance. The ANN model's structure and performance are shown in Figs. 4 and 5, respectively. For the training and testing datasets, Fig. 6 displays a cross-plot illustrating the relationship between the predicted and actual dewpoint pressures by the PSONN model. Table 4 also presents the results of the error analysis for the PSONN model. The model achieved a correlation coefficient of 0.99 and an APRE of 2.47%. Convergence and scatter plots demonstrate strong predictive accuracy.

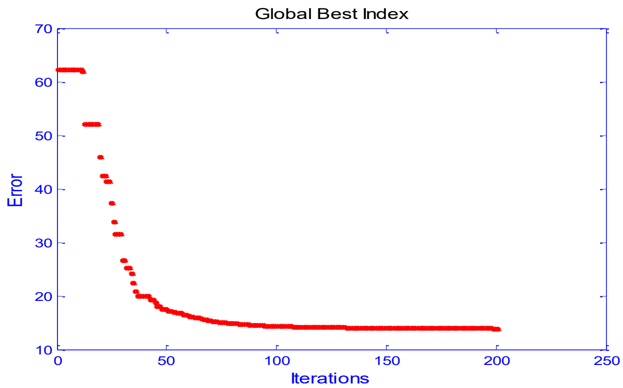


Fig. 3. Comparison of optimization strategies based on convergence.

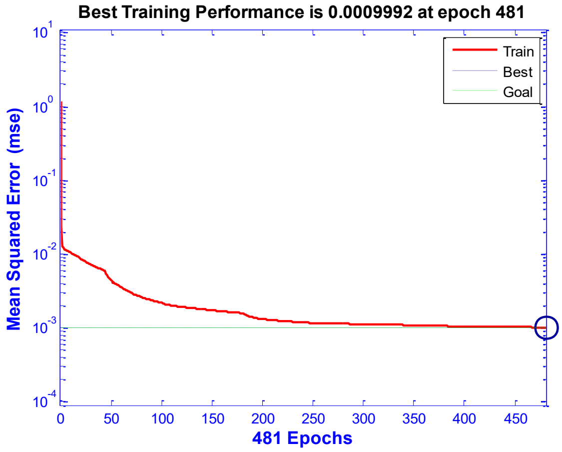


Fig. 4. Convergence of the Particle Swarm Optimization Neural Network during training.

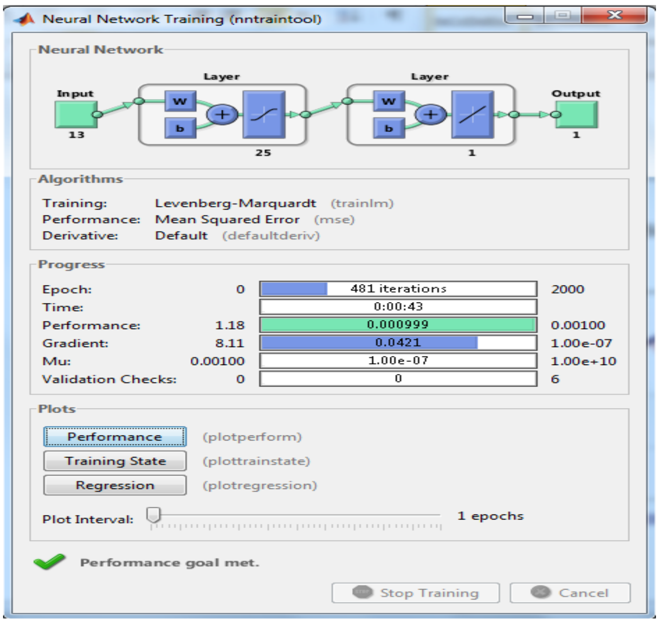


Fig. 5 Training accuracy and loss over epochs for the neural network on Dataset.

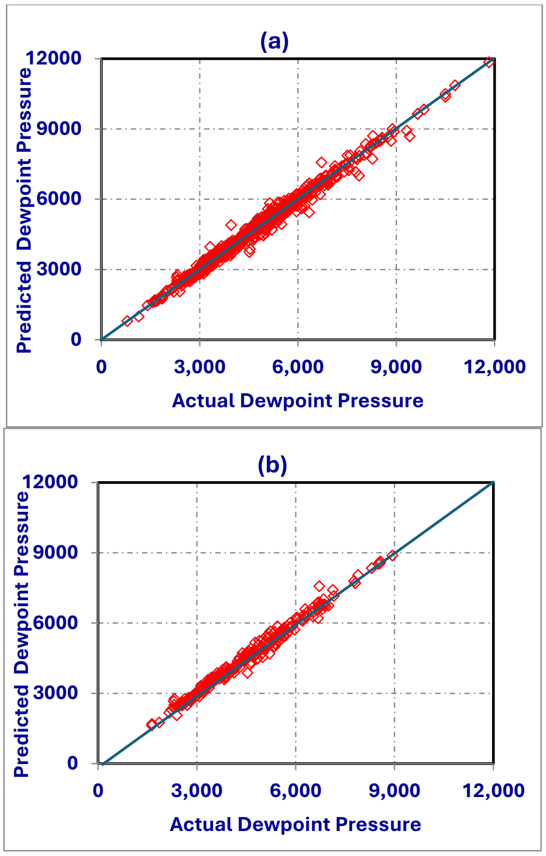


Fig. 6. Scatter plot comparing the PSONN model's predicted values against the actual values-(a)-Training data, (b)-Testing data

*B. NFuzzy Model*

The NFuzzy model was utilized with various radii to predict the dewpoint pressure of condensate gas. Subsequently, the predicted correlation coefficient and absolute percent relative error were plotted against these radii. The most suitable radius was identified as the one yielding the maximum correlation coefficient and the minimum average percentage relative error. As shown in Fig. 7, a radius of 0.25 produced the highest CC value (0.97) and the lowest APRE (5.86%). Fig. 8 shows the number of NFuzzy model rules, and Fig. 9 shows a cross-plot of the actual dewpoint pressure for both the training and testing phases against the projected values derived from the NFuzzy model. For both training and testing datasets, the accuracy results of the NFuzzy model are summarized in Table 4, which displays a prediction error of 8.78% and a correlation coefficient of 0.970.

Table 4 also presents a comparison between the NFuzzy and PSONN models, demonstrating that the PSONN model outperforms the NFuzzy model. Table 6 shows the good prediction performance of PSONN models for both training and testing datasets.

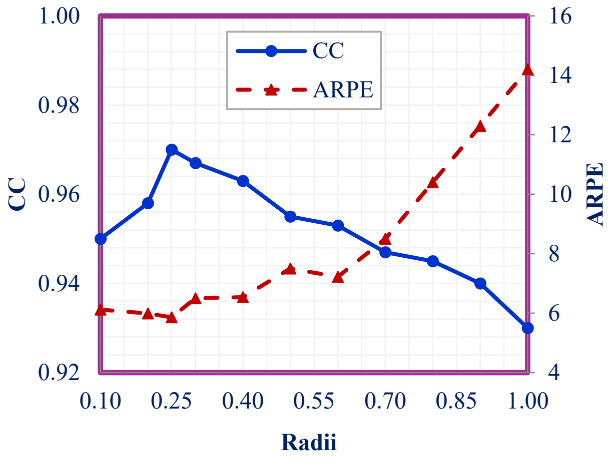


Fig. 7 displays the optimal radii for NFuzzy model.

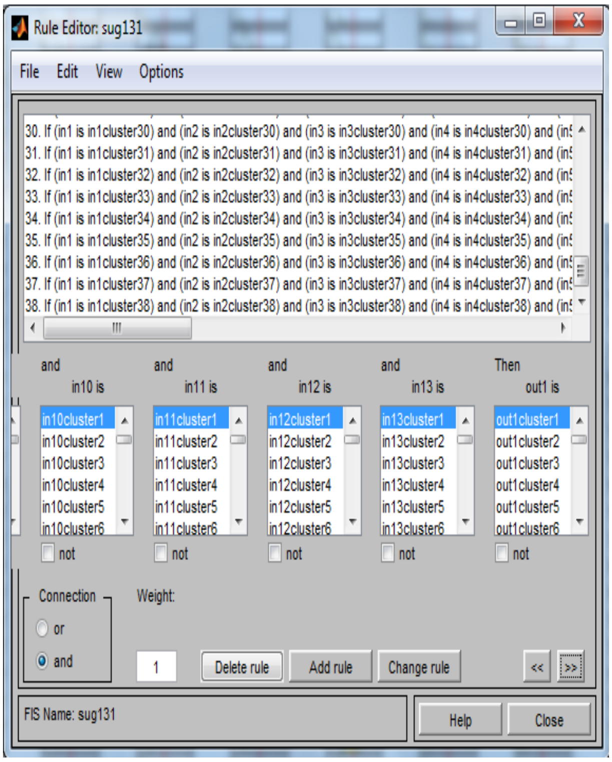


Fig. 8. Depicts of number of NFuzzy model rules

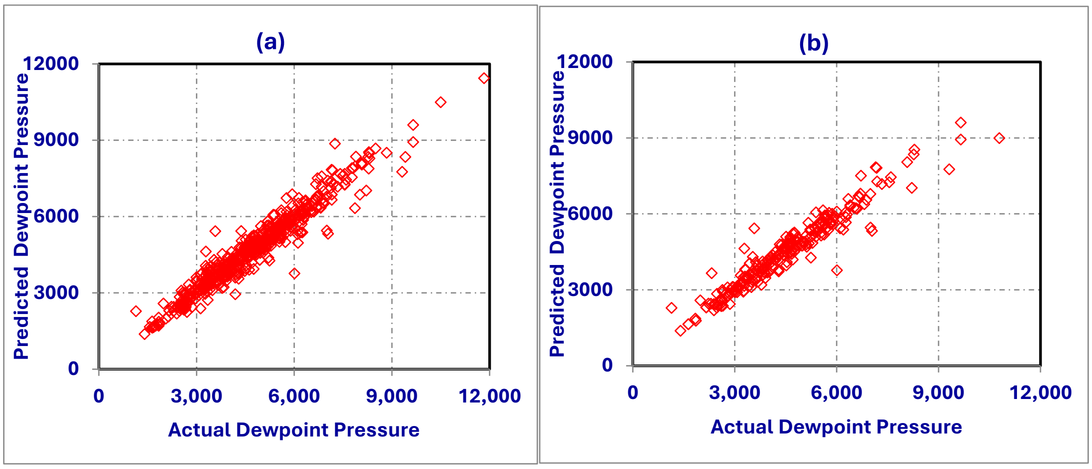


Fig. 9. Shows the cross-plot of NFuzzy model. (a) Training dataset; (b) Testing dataset

TABLE 4. STATISTICAL ERROR ANALYSIS OF BOTH PROPOSED MODELS

| Parameters | NFuzzy Model | | PSONN Model | |
|---|---|---|---|---|
| | Abs. Error | APRE % | Abs. Error | APRE % |
| Maximum | 2241.4 | 59.48 | 936.9 | 23.66 |
| Minimum | 0.42 | 0.01 | 0.02 | 0.00 |
| Average | 259.3 | 5.86 | 110.6 | 2.47 |
| Standard Deviation | 290.7 | 6.54 | 127.9 | 2.76 |
| Root Mean SQR Error | 8.78 | | 3.70 | |
| Correlation Factor | 0.97 | | 0.99 | |

*C. Comparison between Hybrid models and published Models*

Table 5 provides a comparison between 24 published AI models and the proposed models for predicting dewpoint pressure, organized according to the year of publication, utilized models and methods, number of data samples, and Absolute Percent Relative Error. This table presents a diverse range of AI techniques employed by various authors, including GA-ANN, RBF, MLP, ANN, LSSVM, ANFIS, MGGP, and SVM, along with the respective number of data samples utilized in each study.

Although the models in [16, 39] were developed using comparatively smaller datasets, they still delivered remarkably low APREs of 2.41% and 1.55%, respectively. Meanwhile, the model in [51] demonstrated a commendable APRE of 3.660% when applied to a larger dataset comprising 562 samples. However, this model exhibited a significant disparity between training and testing performance, with APREs of 1.997% and 10.287%, indicating inconsistency in predictive accuracy. In studies [30] and [44], various AI techniques were applied to relatively large datasets consisting of 632 and 681 samples. Among the models tested, the most effective ones achieved APRE values of 5.701 and 3.4698, respectively. In contrast, although datasets in [28] and [23] were even larger—comprising 802 and 789 samples—their models produced higher APREs of 8.64 and 9.35, suggesting comparatively reduced predictive accuracy. In this study, we employed the largest databases to develop two hybrid models (NFuzzy and PSONN). Among 24 published AI models, the proposed hybrids—especially PSONN—outperform earlier methods in accuracy and dataset size. PSONN achieves a superior balance of generalization and predictive performance across training and testing phases, as shown in Table 5.

TABLE 5. COMPARES APRE VALUES ACROSS PUBLISHED MODELS FOR PREDICTING DPP.

| Index | Year | Reference | Method | N | AARD (%) |
|---|---|---|---|---|---|
| 1 | 2003 | Gonzalez | MLP | 802 | 8.64 |
| 2 | 2009 | Nowroozi | ANFIS | 110 | 5.13 |
| 3 | 2013 | Arabloo | CSA-LSSVM | 562 | 6.3 |
| 4 | 2013 | Kaydani | LM-MLP | 100 | 5.84 |
| 5 | 2013 | Ghassemzadeh | ANFIS | 111 | 10.52 |
| 6 | 2014 | Ahmadi | LSSVM | 404 | 5.02 |
| 7 | 2014 | Majidi | MLP | 562 | 6.802 |
| 8 | 2014 | Rostami | GA-RBF | 562 | 3.66 |
| 9 | 2015 | Rabiei | ANN | 308 | 3.1315 |
| 10 | 2016 | Kamari | GEP | 562 | 7.9 |
| 11 | 2016 | Kaydani | MGGP | 158 | 4.44 |
| 12 | 2016 | Khaksar | PSONN | N.A. | 3.513 |
| 13 | 2016 | Najafi | GA-RBF | 564 | 7.3 |
| 14 | 2017 | Ahmadi | GEP | N.A. | 8.1 |
| 15 | 2018 | El-hoshoudy | GEP | 480 | 6.72 |
| 16 | 2018 | Zhong | PSO-MKF-SVM | 568 | 7.01 |
| 17 | 2019 | Khan | ANN | 82 | 2.41 |
| 18 | 2020 | Ali | ANFIS | 168 | N.A. |
| 19 | 2020 | Daneshfar | MLP | 81 | 1.553 |
| 20 | 2020 | Haji-Savameri | MLP-BR | 632 | 5.701 |
| 21 | 2021 | Mirzaie | AI | 681 | 3.4698 |
| 22 | 2022 | Gouda | ANN | N.A. | N.A. |
| 23 | 2022 | Luo | GA-ANN | 721 | N.A. |
| 24 | 2023 | Zohre | DT | 789 | 9.35 |
| 25 | 2024 | This study | NFuzzy | 860 | 5.86 |
| 26 | 2025 | This study | PSONN | 860 | 2.47 |

Compared to 24 AI models from the literature—which vary in dataset size (81 to 802 samples) and APRE range (1.55% to >9%)—the proposed hybrid models, developed on the largest dataset (860 samples), achieve superior prediction accuracy with PSONN exhibiting an APRE of 2.47%, demonstrating improved generalization against previous methods.

TABLE 6. Estimation errors for predicting the DPP using NFuzzy and PSONN models.

| Database | NFuzzy Model | PSONN Model | Data Samples |
|---|---|---|---|
| | APRE% | APRE% | |
| Training Data | 5.84 | 2.37 | 602 |
| Testing Data | 5.89 | 2.68 | 258 |
| All Data | 5.86 | 2.47 | 860 |

## V. Conclusions

- The proposed PSONN model achieved state-of-the-art predictive accuracy, with an APRE of 2.47% and a correlation coefficient of 0.99, surpassing all previous AI-based models for DPP prediction.
- The hybridization of Particle Swarm Optimization with an Artificial Neural Network successfully synergized the strengths of both algorithms, overcoming their individual limitations to produce a more robust and accurate model.
- Both introduced models demonstrated a well-balanced performance between training and testing phases, indicating a high generalization capability and a low risk of overfitting.
- The use of a larger, more comprehensive dataset compared to prior studies significantly improves the reliability and validity of the model's results.
- Future work should focus on continually expanding the dataset with information from diverse gas fields to further improve and validate the model's generalizability.

### List of Symbols

| | | | |
|---|---|---|---|
| APRE | Absolute Percent Relative Error | Ei | Residual Error |
| C1 | Methane concentration (Fraction) | H2S | Hydrogen sulphide concentration (Fraction) |
| C2 | Ethane concentration (Fraction) | MWC7+ | Molecular weight of heptane plus fraction (g/mol) |
| C3 | Propane concentration (Fraction) | N2 | Nitrogen gas concentration (Fraction) |
| C4 | Butane concentration (Fraction) | RMSE | Root mean squared error |
| C5 | Pentane concentration (Fraction) | SD | Standard deviation |
| C6 | Hexane concentration (Fraction) | SGC7+ | The specific gravity of heptane plus fraction |
| C7+ | Heptane plus concentration (Fraction) | T | Temperature (oF) |
| CO2 | Carbon dioxide concentration (Fraction) | Y | Actual Data |
| CC | Coefficient of determination | Ypred | Predicted Data |
| DPP | Dew point pressure (psi) | n | Number of data |
| *X* | Dimension | I | input |
| H | hidden | HO | Hidden output |
| O | Output | HI | Hidden input |

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