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New Correlations of Dew-Point Pressure for Gas Condensate Reservoirs Using Hybrid Modelling

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Abstract

For the development of gas condensate reservoirs and the handling of gas condensate fluids, the dew-point pressure (DPP) is an essential characteristic. Many individual mathematical relationships and intelligent systems were also used to predict this property with a good accuracy, but applying the hybrid models is fewer. For these reasons, nonlinear multiple regression (NLMR) approach and hybrid intelligent models were proposed to predict dew-point pressure accurately. This hybrid technique is Particle Swarm Optimization with Neural Networks (PSO-NN). Around of 900 collected data points are utilized to develop these hybrid models. The temperature (T), the composition of hydrocarbon, specific gravity (SG) and molecular weight (Mw) of heptane plus were used as inputs to predict the dew-point pressure (DPP).

The performance of the both NLMR approach and PSO-NN model are compared with performance of the most published empirical correlations and artificial intelligences (AI) models in the literature. Based on the statistical error analysis results, the new hybrid PSO-NN models outperform the NLMR model and the most published empirical correlations and artificial intelligences (AI) in the literature. The result also confirmed the PSO-NN hybrid model achieved the best one with APRE (2.45%) and the highest CC (0.997).

Keywords: Artificial intelligences, Nonlinear multiple regression, Hybrid; PSO-NN, Dew-point Pressure.

علاقات ارتباطية جديدة لضغط نقطة الندى في مكامن الغاز المتكثف باستخدام النمذجة الهجينة

الخلاصة:

يُعد ضغط نقطة الندى (Dew-Point Pressure, DPP) من الخصائص الأساسية في تطوير مكامن الغاز المتكثف وإدارة موائع الغاز المتكثف. وقد استُخدمت العديد من العلاقات الرياضية المنفردة وتقنيات الأنظمة الذكية للتنبؤ بهذه الخاصية بدقة جيدة، إلا أن تطبيق النماذج الهجينة في هذا المجال ما يزال محدوداً نسبياً. لذلك، تقترح هذه الدراسة استخدام أسلوب الانحدار المتعدد غير الخطي (Nonlinear Multiple Regression, NLMR) ونماذج ذكية هجينة للتنبؤ بدقة بضغط نقطة الندى. وتعتمد التقنية

الهيمنة المقترحة على دمج خوارزمية تحسين سرب الجسيمات (Particle Swarm Optimization, PSO) مع الشبكات العصبية الاصطناعية (Neural Networks, NN)، فيما يُعرف بنموذج (PSONN). تم استخدام ما يقارب 900 نقطة بيانات جُمعت من مصادر مختلفة لتطوير هذه النماذج الهيمنة. وقد استخدمت درجة الحرارة (T)، وتركيب الهيدروكربونات، والكثافة النوعية (SG)، والوزن الجزيئي (Mw) لمركب الهيبنتان وما فوقه (C7+) كمتغيرات إدخال للتنبؤ بضغط نقطة الندى (DPP). كما جرت مقارنة أداء كل من نموذج الانحدار المتعدد غير الخطي (NLMR) والنموذج الهجين (PSONN) مع أداء أبرز العلاقات الارتباطية التجريبية ونماذج الذكاء الاصطناعي المنشورة في الأدبيات العلمية. وأظهرت نتائج التحليل الإحصائي للأخطاء أن نماذج (PSONN) الهيمنة المقترحة تفوقت على نموذج (NLMR) وعلى معظم العلاقات الارتباطية التجريبية ونماذج الذكاء الاصطناعي المنشورة سابقاً. كما أكدت النتائج أن نموذج (PSONN) حقق أفضل أداء، حيث سجل متوسط الخطأ النسبي المطلق (APRE) مقداره 2.45%، بالإضافة إلى أعلى معامل ارتباط (CC) بلغت قيمته 0.997، مما يدل على دقة تنبؤية عالية وموثوقية كبيرة في تقدير ضغط نقطة الندى لمكامن الغاز المتكثف.

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. Although, these methods take along complex computation, they have not achieved enough accuracy [2].

Understanding the dew-point pressure is essential because it helps determine the behavior of the gas condensate reservoir and the conditions under which condensate will start to separate from the gas phase [3]. It indicates the pressure level at which the condensate will start to accumulate in the reservoir, leading to changes in fluid flow and production characteristics [4].

Dew-point pressure is an important property in characterizing the gas condensate reservoirs. The first published dew-point pressure correlation can be dated back to 1947 by Sage and Olds [5]. Certainly, over the past three decades, there has been a growing interest in developing new correlations for dew-point pressure obtained from different regions around the world [6]. These correlations aim to establish relationships between various properties of crude oil, such as density, temperature, API gravity, and other compositional characteristics [7-10] as follows:

$$\ln(DPP) = A_1([XC]^2 + [XCO]^2 + [XH]^2 S + [XC]^6 + 2([XC]^3 + [XC]^4) + [XC]^5 + 0.4XC^1 + 0.2XN^2 + A^2 YC^{(7+)} + A^3 ((XC^1) / X^{(7+)} + 0.002) + A^4 Tf + A^5 (XC^{(7+)} + MWC^{(7+)}) + A^6 (XC^{(7+)} + MWC^{(7+)})^2 + A^7 (XC^7 + MWC^{(7+)})^3 + A^8 [MWC^{(7+)} \setminus Yc^{(7+)} + 0.0001] + A^9 [MWC^{(7+)} \setminus Yc^{(7+)} + 0.0001]^2 + A^{10} + A^{10} [MWC^{(7+)} \setminus Yc^{(7+)} + 0.0001]^3 + [A^1]^1 \quad (1)$$

Where: $A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}$ and A_{11} are coefficients [1].

$$\ln(DPP) = \beta_0 + \beta_1 \ln(T_R) + \beta_2 \ln(R_m) + \beta_3 \ln(P_{SP} \cdot T_{SP}) + \beta_4 / T_{pr} + \beta_5 / P_{pr} + \beta_6 / \gamma_{C7+} \quad (2)$$

Where: $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ and R_m are coefficients [2].

$$DPP = A_0 + A_1 T_f + A_2 H_2S + A_3 CO_2 + A_4 N_2 + A_5 C_1 + A_6 C_2 + A_8 C_4 + A_9 C_5 + A_{10} C_6 + A_{11} C_{7+} + A_{12} MW_{C_{7+}} + A_{13} \gamma_{C_{7+}} + A_{14} (C_{7+} MW_{C_{7+}}) + A_{15} \left(\frac{MW_{C_{7+}}}{\gamma_{C_{7+}}} \right) + A_{16} \left(\frac{XC_{7+} MW_{C_{7+}}}{\gamma_{C_{7+}}} \right) + A_{17} \left(\frac{XC_{7+}}{(XC_1 + XC_2)} \right) + A_{18} (XC_{7+} / XC_3 + XC_4 + XC_5 + XC_6) \quad (3)$$

Where: $A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}, A_{15}, A_{16}, A_{17}$ and A_{18} are coefficients [3].

$$DPP = K_1 * \left[\frac{GOR^{K_2}}{C_7^{K_3}} * K_8 * API^{(K_4 * Tr^{K_5} - K_6 * C_7^{K_7})} \right] \quad (4)$$

Where: $K_1, K_2, K_3, K_4, K_5, K_6, K_7$ and K_8 are coefficients. See [4].

$$DPP = B_1 + B_2 + B_3 + B_4 \quad (5)$$

Where: B_1, B_2, B_3 and B_4 , are coefficients [5].

$$DPP = A_0 + A_1 B_1 + A_2 B_2 + A_3 B_3 + A_4 B_4 + A_5 B_5 + A_6 B_6 + A_7 B_7 + A_8 B_8 + A_9 B_9 + A_{10} B_{10} + A_{11} B_{11} + A_{12} B_{12} + A_{13} B_{13} + A_{14} B_{14} + A_{15} B_{15} \quad (6)$$

Where: $B_1, B_2, B_3, B_4, B_5, B_6, B_7, B_8, B_9, B_{10}, B_{11}, B_{12}, B_{13}, B_{14}, B_{15}, A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}$ and A_{15} , are coefficients [6].

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

See [7] to find A and B.

$$DPP = -888.278 - T \times (C_1 \times 3.60639 + T \times 0.00785623) + C_1 \times 1467.87 + A \times 0.989073 \quad (8)$$

Where: A, B, C [8].

$$DPP = -888.278 - T \times C_1 \times 3.60639 + (T)^2 \times 0.00785623 + C_1 \times 1467.87 + A \times 0.989073 \quad (9)$$

Where: A, B, C [9].

$$DPP = (I_1 + I_2 + I_3 + I_4 + I_5) / 145.038 \quad (10)$$

Where: I_1, I_2, I_3, I_4 and I_5 are coefficients. See [10].

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 [11] was developed to predict the DPP of condensate gas reservoirs using 802 data samples. Different ANN models [12] were proposed for predicting DPP using 111 data sets. 113 data points were used to develop an ANN technique gathered from Middle East reservoir [13,15]. The ANN technique obtained the best results. Also, different ANN models were proposed for predicting DPP [15,16]. Fuzzy model and expert systems were developed to predict a gas condensate dewpoint pressure using gas composition and reservoir temperature [17,18]. Different intelligent systems [19] 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 [20]. 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 [21]. Gene expression programming with multiple regression analysis were combined for estimating the DPP in gas condensate [22]. 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 [23]. Adaptive neuro-fuzzy approach, hybrid soft computing approaches and hybrid intelligent approaches models were comprised for predicting DPP of gas condensate reservoirs [24-26]. 721 data points were used to develop artificial neural network (ANN) models with combining GA and PSO to predict DPP [27]. Different machine learning models and Multilayer Perceptron Neural Network developed for predicting DPP using 681 published data samples [28,29].

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 [30-33]. Hybrid models, such as those combining neural networks with optimization algorithms like PSO, further improve predictions for oil well output and energy [34-36]. 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 [37-39].

1.1. Data Acquisition

For this study, the database was firstly gathered from literature and the others from the reported experimental data. Around of 880 data samples were collected for developing the two hybrid models. These data include 880 measured data collected data points collected from Middle East

fields. This database is larger than those used in the other previously published studies. These data samples are firstly prepared by checking the data ranges, duplicate values and missing data.

Table (1) depicts the ranges of all gas condensate parameters. The input of these data included temperature T, molecular weight heptane plus, specific gravity C_{7+} , 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 samples were used to train and test the proposed models respectively. In addition, 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): Depicts the ranges of Gas Condensate database

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

2. 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 (PSO-NN), and statistical error analysis were utilized to calculate the dew-point pressure of gas condensate reservoirs as following:

2.1. Nonlinear Multiple Regression (NLMR) model

Nonlinear multiple regression is a statistical technique used to model the relationship between multiple independent variables and a dependent variable when the relationship is nonlinear. 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 of this study is shown in Figure (1).

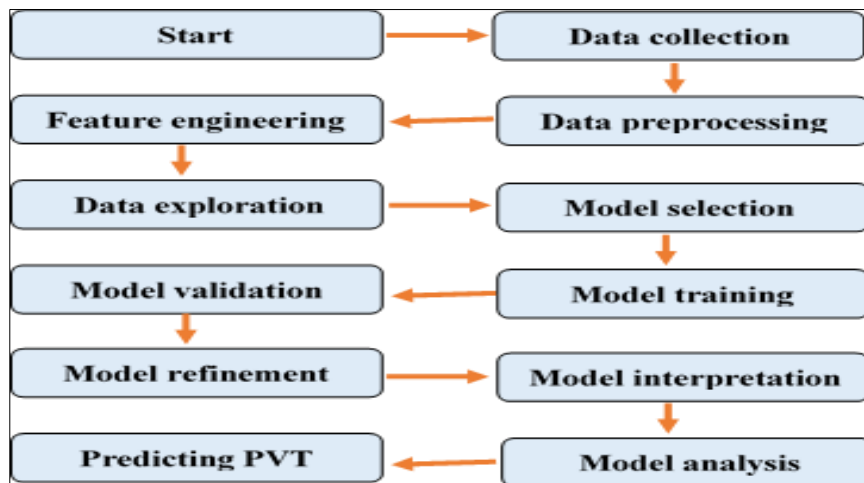


Fig. (1): The proposed workflow for this study

2.2. Particle Swarm Optimization (PSO)

PSO is a robust algorithm 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.

2.3. Particle Swarm Optimization with Neural Networks (PSO-NN)

Although ANN has a high degree of accuracy in handling nonlinear problem, it has many weaknesses. The main problems of ANN model are the slow convergence, local minimum point and determination both the number of hidden layers and number of hidden layer neurons. 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. Therefore, it is essentially to combine the PSO algorithm with ANN model to achieve faster convergence and higher accuracy. In addition, combining ANN model with PSO algorithm can overcome the weakness of both algorithms.

2.4. 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), Standard Deviation (SD) and the correlation coefficient (CC) as shown in Table (2).

Table (2): Type of error analysis used in this study

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

3. New Approaches Development

3.1. 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). 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:

$$DDP = \left(\frac{A}{B}\right) + \left(\frac{D}{E}\right) \quad (11)$$

Where:

$$A = 14.37 - 4.87 \times C_1 + 112.08 \times C_2 - 0.00001 \times C_4 + 70.7 \times (C_4)^2 + 909.9 \times C_5 - 21891 \times C_6 + 353.8 \times H_2S - 0.049 \times (T + 460), \quad B = 0.0014 \times (T + 460) + 0.1257, \quad D = 6626.39 + 43.647 \times C_1 \times M_W - 5760.65 \times C_3 - 23159.99 \times C_{7+} + 1791.075 \times \ln(C_{7+}) + 5078.48 \times CO_2 + 7079.373 \times N_2, \quad E = (1.704 - SG)$$

3.2. 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): illustrates 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:

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

4. Results and Discussion

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.

Figure (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. The best training performance of the PSONN model is showed in Figure (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. Figure (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 Figure (5). Similar to Figure (4) but specifically for the nonlinear multiple regression (NLMR) model, demonstrating its predictive capability through predicted vs actual cross-plot. Figure (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). Figure (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.

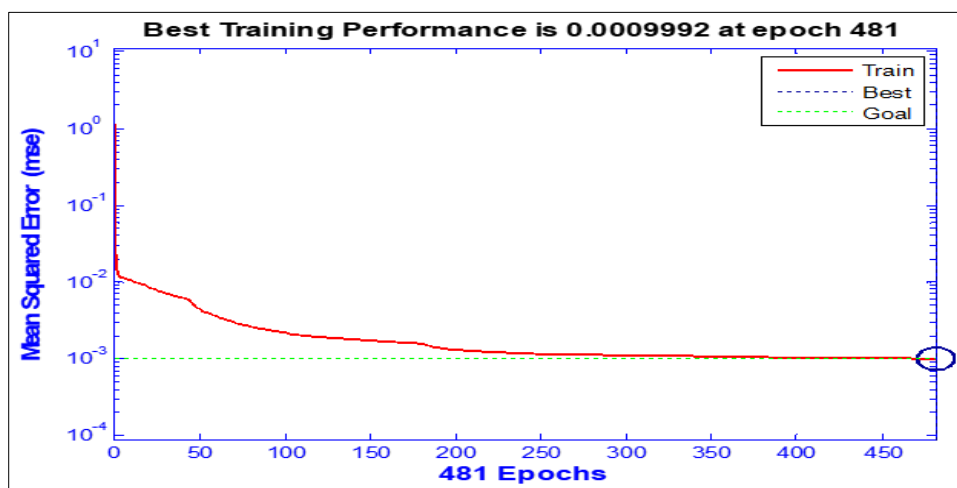


Fig. (2): The best performance of PSO technique

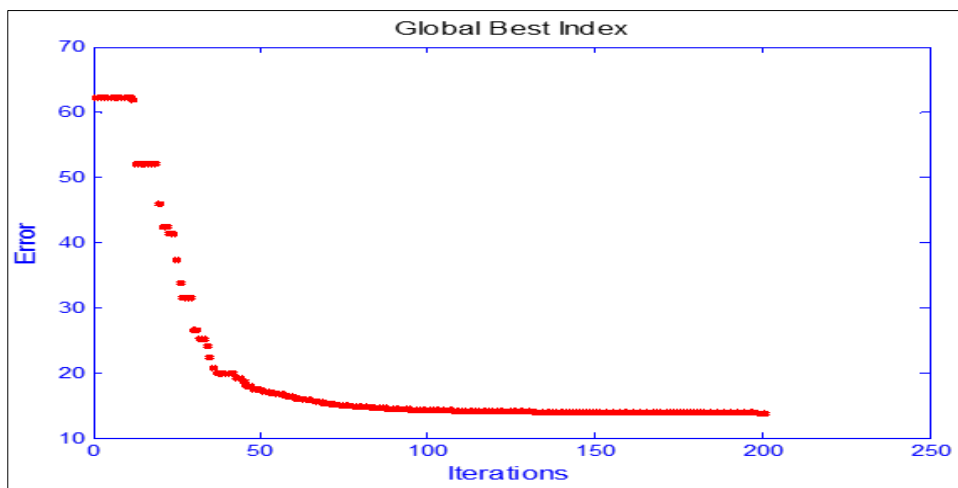


Fig. (1): The best training performance of the PSOMN model

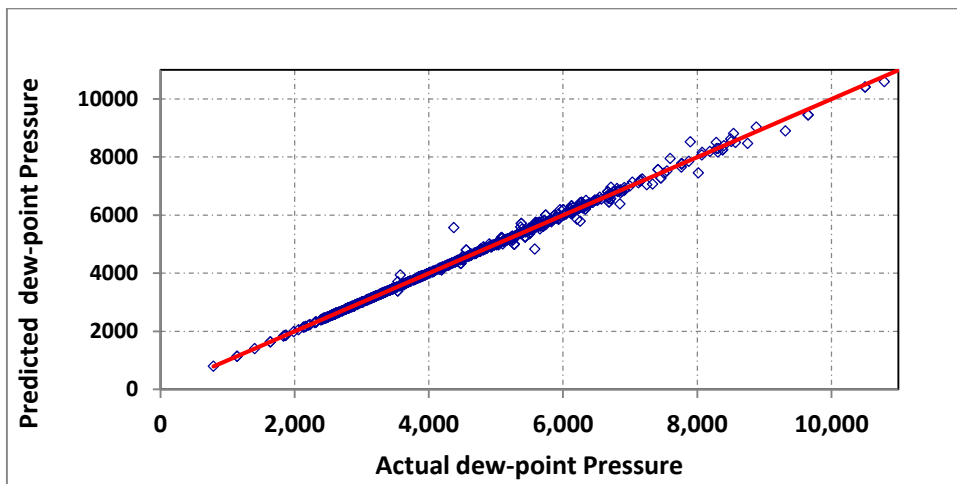


Fig. (2): The cross-plot of PSO model

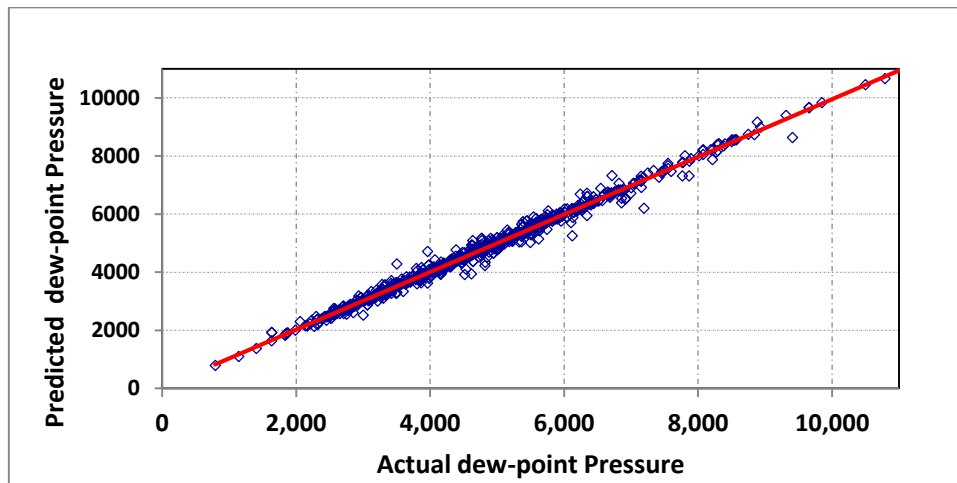


Fig. (3): The cross-plot of NLMR model

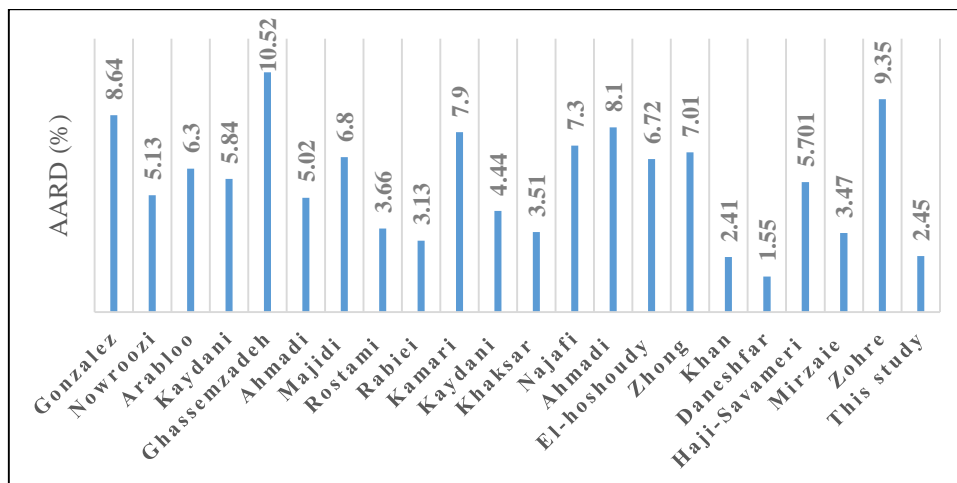


Fig. (4): Comparing the published AI models to proposed models for predicting DPP

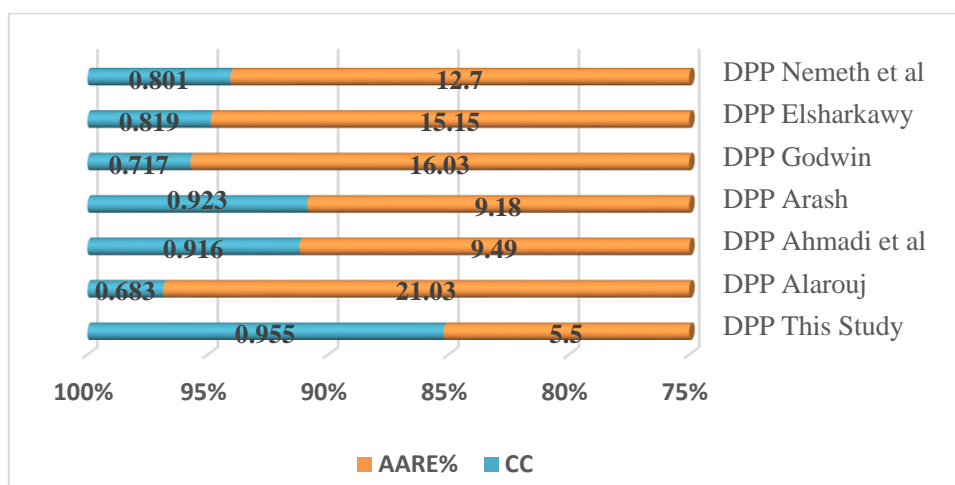


Fig. (5): Comparing of the AARE and CC for the developed NLMR DPP correlation in this study and the published DPP correlations

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.

Model developed by Khan has achieved excellent APRE values with 2.41% and 1.553 respectively; but they have just used fewer data samples comparing to others 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 Zohre used a larger dataset with 802 and 789 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. Tables 4 and 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 published AI models to proposed models for DPP.

Index	Year	Reference	Method	N	AARD (%)
1	2003	Gonzalez	MLP	802	8.64
2	2009	Nowroozi	ANFIS	110	5.13
4	2015	Hamada et al	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	ANN-PSO	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	2022	AlGathe et al	PSO-MKF-SVM	568	7.01
17	2019	Khan	ANN	82	2.41
18	2020	Ali	ANFIS	168	N.A.
20	2020	Haji-Savameri	MLP-BR	632	5.701
21	2021	Mirzaie	AI	681	3.4698
23	2022	Luo	GA-ANN	721	N.A.
24	2023	Zohre	DT	789	9.35

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

5. Conclusions

The main conclusions of this study are as follows:

- For gas condensate reservoirs, new dew-point pressure (DPP) correlations have been created using NLMR approach and PSONN technique.

- 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 PSONN and NLMR proposed models outperformed the published models in the previously literature.
- Both proposed models showed a respectable balance between the training and testing APRE (%) values.
- 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.

List of symbols

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

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