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Petroleum & Petrochemical Engineering Journal
ISSN: 2578-4846

Prediction of Dew Point Pressure in Gas Condensate Reservoirs Based on a Combination of Gene Expression Programming (GEP) and Multiple Regression Analysis

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Research Article

Volume 2 Issue 3

Received Date: June 29, 2018

Published Date: July 12, 2018

DOI: 10.23880/ppej-16000163

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Abstract

Gas condensate reservoirs represent unique and clean hydrocarbon source of energy, so prediction of their thermodynamic criteria especially dewpoint pressure (P_d) is crucial for reservoir characterization and management, since declining of initial reservoir pressure below dewpoint pressure result in liquid built up near wellbore and reduce gas productivity index. In this study, a mathematical modeling developed to estimate dewpoint pressure at reservoir temperature using reliable, precise, well-organized gene expression programming (GEP) approach in combination with multiple non-linear regression analysis. The dataset comprises 453 published data points, and the model developed as a function of compositional analysis of hydrocarbons components (Z_{C1}-Z_{C7+}), physical properties of heptane plus fractions (C_{7^+}) including molecular weight and specific gravity, the mole fraction of nonhydrocarbons (Z_{CO2}& Z_{N2}) and reservoir temperature. Experimental Pressure-Volume-Temperature (PVT) analysis including constant composition expansion (CCE) at reservoir conditions and compositional analysis are carried out through 27 gas condensate samples not used in model development, and covering a great range of PVT properties to evaluate the new predictive model accuracy. Assessment and validation of the developed and published correlations carried out by a statistical and graphical error analyses. The obtained relative errors indicate that the developed model employed as an alternative approach monitoring the dewpoint pressure of gas condensate reservoirs when the required real data are not accessible.

Keywords: Retrograde gas reservoirs; Dewpoint pressure; Gene expression programming (GEP); Genetic Algorithm (GA); Regression analysis; Empirical correlation

Introduction

Retrograde gas reservoirs recognized as one of the most precious, and clean hydrocarbon energy sources in comparison to other fossil fuels [1-7]. They differ in their thermodynamic and flow behavior from other common gas reservoirs [8] since they exist as a gas phase at initial reservoir pressure [6], where the reservoir temperature lies between critical temperature (T_c) and cricondentherm temperature (T_{ct}). By pressure declining below dewpoint pressure during "Flow-in" process, these reservoirs begin to condense isothermally until reach to separator conditions. By further pressure reduction, the liquid volume reaches a maximum value called maximum liquid drop out (LDO) at a certain pressure, then begins to vaporize [8]. One of the most characteristic physical parameters for gas condensate reservoirs is the dewpoint pressure, which defined as the pressure where a massive amount of gas phase is in equilibrium with a negligible volume of liquid phase [9] or qualitatively defined as the pressure at which the first droplet of condensate begins to condense [5]. Typical phase diagram of gas condensate is shown in Figure 1. By reducing pressure isothermally starting from point "1", condensation begins at point "2" (dewpoint pressure) [4,10,11] and reach a maximum at point "3" then begins to decrease [12]. Point "G" represents separator condition that lies in the two-phase region, in which well stream separated into separator gas and separator oil [13]. Dewpoint pressure of the gas condensate reservoirs either detected in the lab during constant composition expansion test (CCE) [4] or estimated from empirical relations [14]. Petroleum engineers may resort to empirical correlation in case of; non-representative samples, unavailability of PVT analyses [15], quality check of lab analysis, expensive analysis cost [16,17]. Empirical correlations usually developed for district geographic provinces with given chemical composition of reservoir fluid and data range [16,18]. Thus, generalized accurate PVT relations are rare. Most empirical PVT relations were developed by multiple linear or non-linear regression techniques in addition to graphical techniques [16,19,20]. Several studies reported about the effect of dewpoint pressure on the well productivity in gas condensate reservoirs [21-25] and concluded that gas productivity, relative permeability, and gas recovery decrease below dewpoint pressure as condensate buildup increases around wellbore [5]. Therefore, estimation of dewpoint pressure is decisive for fluid characterization and management of gas condensate reservoirs [5,26]. Moreover, several mathematical models, equations of state and empirical correlations reported the estimation of dewpoint theoretically [6,9,27].

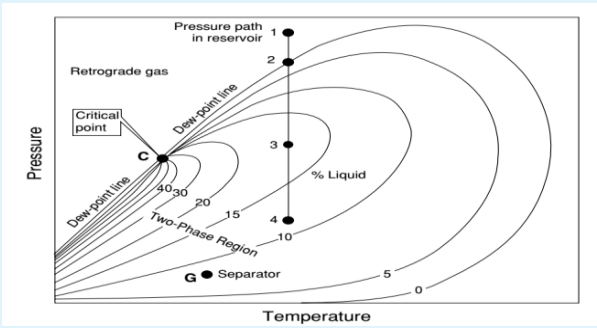


Figure 1: Phase behavior of gas condensate reservoirs.

Numerous empirical correlations are widely reported for dewpoint prediction; Eilerts and Smith [25] developed four correlations relate dewpointpressures to temperature, composition, molar average boiling pointand gas-to-oil ratio [28,29]. Olds, et al. [30] estimate the dewpoint pressure as a function of the gas-oil ratio (GOR), temperature, and stock tank oil gravity (API) for Palomafield [5] and represented their correlation in a graphical and tabular form [26]. Reamer and Sage [31] estimate dewpoint pressure as a function of the reservoir temperature and gas-oil ratio (GOR) in Louisiana field. Organickand Golding [31] estimate dew point pressure in the form of 14 working charts [32] for gas condensate systems with a relative error of 8% [5,8]. Nemeth and Kennedy [33] develop empirical correlation based on 579 data set to predict dewpoint pressure by multiple regression analysis based on temperature, molecular weight, the specific gravity of C_{7^+} and fluid compositions [4]. Crogh [34] presented a correlation by neglecting reservoir temperature in the Nemeth and Kennedycorrelation[33] in order to have a better prediction of dewpoint pressure. Carlson and Cawston [35] study the effect of non-hydrocarbon impurities, especially H_2S on the dewpoint pressure in the Brazeau River area of Alberta, Canada and concluded that increasing of H_2S content reduces liquid dropout volume [5]. Potsch and Braeuer [36] determine the dewpoint pressure as a function of Z-factor through a graphical model. Fang, et al. [37] develop a new empirical correlation which predicts the dewpoint pressure of gascondensate as a function of gas composition, temperature, heptane-plus fraction (C_{7^+})characteristics and average molecular weightof fluid mixture [28]. Humoud andAlMarhoun [38] utilize multi-regression

techniques to develop an empirical model for gas condensate samples extracted fromthe Middle East region [5]. Their correlation developed as a function of reservoir temperature, pseudo reduced pressure and temperature, separator gas/oil ratio, separator pressure and temperature, relative densities of separator gas and the heptane-plus fraction [28], with an average absolute error of 4.3%, and a maximum relative error of 15.1% [26]. Marruffo et al. [39,40] proposed a mathematical model to predict dewpoint pressure and C_{7^+}characteristics ofgas condensate reservoirs using146 PVT data points through nonlinear regression software from Western Venezuela (Anaco) fields [5]. Elsharkawy [41] develop an empirical model which predict dewpoint pressure based on 340 measured data point as a function of molecular weight, temperature, fluid composition, and specific gravity of C_{7^+} components. Al-Dhamen and Al-Marhoun [42] use the artificial neural network to develop a new correlation as a function of reservoir temperature, gas/oil ratio,gas and oil specific gravity. Shokir [9] use 245 data set and apply mathematical genetic approach and orthogonalleast squares algorithm to predict dewpoint pressure as a function of reservoir fluid composition and reservoirtemperature [28] neglecting specific gravity of C_{7^+}. Godwin [43] used 259 gas condensate sample covering a wide range of gas properties and develop a new model predicting dewpoint pressure as a function of gas composition analysis and reservoir temperature with an average relative error of 0.0488% and absolute average relative error of 0.099%. Wang, et al. [44] predict dewpoint pressures of gas condensate reservoirs as a function of reservoir temperature, gas composition and physical properties of C_{7^+} component based on 14 group of gas condensate samples in China. Kaydani, et al. [28] develop a new correlation based on multi-gene genetic programming to determine dewpoint pressure of gas condensate reservoirs. Kamari, et al. [8] develop a new modelfor predicting dewpoint pressure in gas condensate reservoirs using gene expression soft-computing programming, based on 562 experimental data set from constant volume depletion (CVD) tests. Ahmadi and Elsharkawy [32] develop a correlation to estimate the dewpoint pressure in gas condensate reservoirs using gene expression programming (GEP).

Owing to complex relations between composition and dewpoint pressure [45], itis not practical to develop a universal global correlation to predict thisparameter as stated in the literature [29,31,46]. Moreover, the experimental determination of dewpoint pressure for the gas condensate fluid at reservoir temperature is relatively expensive andtime-consuming [2,27,28,30,41,47]. This led the authors in this study to build up a novel relation using gene expression programming (GEP) as a soft computing approach in combination with multiple least squares non-linear regression analysis to predict dewpoint pressure for retrograde gas condensate reservoirs based on the published data covering a wide range. Moreover, the accuracy of the developed correlations as compared to the widely well-known published ones determined through statistical error analysis, then correlation validated by other 27experimentally measured dataset not used in model development.

Experimental PVT analysis

Dewpoint pressure determined experimentally in our PVT-lab through constant composition expansion (CCE) test. This test carried out to simulate the pressure-volume relations of the hydrocarbon systems [48]. The measured results are summarized in Table 1. The procedure reported in detail through literature [49,50] with minor modification and can be concluded as follow; a portion of the reservoir fluid sample was charged to the automated mercury free Vinci-PVT cell then, subjected to the reservoir temperature and excess of initial reservoir pressure. CCE test carried out by pressure declining isothermally without mass change where the dewpoint pressure and corresponding volume were recorded by running the Macro-built in Software and the retrograde liquid drop out detected by Interface Detection System (IDS). Composition analysis determined according to ASTM 1945 [51], using Clarus 500 Perkin Elmer gas chromatograph in line with the condensate cell utilizing four packed columns connected in series with thermal conductivity detector and capillary column matched with flame ionization detector. Helium used as a carrier gas and the oven isothermal temperature adjusted at 100°C in order to provide highly efficient detection of aromatics and paraffin's (normal and isomers) up to heptane plus fractions, in addition to non-hydrocarbon components (N_2,H_2S & CO_2).

#	P_d, psia	T res, F	Mole Fraction									SG -C_{7+}	M.Wt- C_{7+}
			C_1	C_2	C_3	C_4	C_5	C_6	C_{7+}	N_2	CO_2		
1	2845	290	0.705	0.108	0.089	0.031	0.009	0.008	0.005	0.000	0.045	0.776	129.139
2	3415	318	0.881	0.023	0.008	0.005	0.003	0.003	0.006	0.000	0.071	0.789	149.595
3	3850	318	0.858	0.024	0.009	0.007	0.005	0.006	0.016	0.001	0.074	0.789	150.024
4	3631	318	0.811	0.041	0.011	0.007	0.005	0.005	0.006	0.000	0.113	0.788	147.486
5	2640	300	0.785	0.090	0.040	0.020	0.006	0.007	0.022	0.001	0.029	0.790	151.669
6	4153	279	0.669	0.111	0.042	0.015	0.010	0.021	0.082	0.000	0.049	0.812	168.908
7	1986	155	0.817	0.073	0.053	0.029	0.010	0.005	0.010	0.001	0.002	0.779	134.739
8	2056	161	0.857	0.062	0.037	0.018	0.008	0.004	0.005	0.000	0.009	0.790	145.129
9	2268	162	0.800	0.064	0.051	0.029	0.012	0.013	0.026	0.000	0.004	0.788	143.462
10	4275	296	0.808	0.069	0.022	0.009	0.003	0.003	0.011	0.000	0.075	0.788	130.441
11	5120	311	0.765	0.067	0.033	0.021	0.010	0.011	0.043	0.000	0.051	0.794	154.946
12	3852	278	0.761	0.090	0.048	0.019	0.005	0.004	0.016	0.000	0.056	0.788	144.801
13	3305	317	0.754	0.107	0.047	0.020	0.008	0.005	0.023	0.000	0.036	0.778	126.803
14	3281	278	0.711	0.105	0.061	0.030	0.012	0.010	0.041	0.001	0.029	0.796	156.507
15	3950	279	0.619	0.124	0.083	0.033	0.012	0.014	0.069	0.001	0.046	0.799	159.594
16	4382	267	0.838	0.053	0.025	0.014	0.007	0.007	0.027	0.001	0.029	0.797	157.715
17	3500	220	0.910	0.040	0.017	0.008	0.003	0.003	0.012	0.002	0.007	0.802	147.669
18	2853	212	0.857	0.058	0.033	0.018	0.007	0.007	0.011	0.000	0.009	0.787	141.940
19	3285	211	0.832	0.061	0.031	0.018	0.009	0.012	0.029	0.000	0.008	0.789	144.503
20	2321	186	0.799	0.073	0.049	0.024	0.011	0.012	0.028	0.001	0.002	0.780	133.709
21	1139	162	0.828	0.076	0.052	0.025	0.009	0.004	0.006	0.001	0.000	0.776	130.481
22	5495	214	0.918	0.035	0.014	0.008	0.004	0.004	0.013	0.000	0.004	0.801	161.772
23	2205	160.2	0.925	0.033	0.020	0.009	0.003	0.002	0.004	0.000	0.004	0.786	140.389
24	3321	181.76	0.899	0.043	0.023	0.013	0.005	0.004	0.011	0.000	0.002	0.791	152.153
25	2534	170.6	0.961	0.018	0.009	0.005	0.002	0.002	0.003	0.000	0.001	0.790	149.387
26	3500	192.8	0.911	0.034	0.021	0.010	0.005	0.006	0.011	0.000	0.002	0.793	149.035
27	2900	182.4	0.934	0.030	0.014	0.007	0.003	0.003	0.007	0.000	0.001	0.795	152.763

Table 1: Measure PVT Data.

Correlation Built Up and Computation Method

Recently, genetic algorithm (GA) used to solve mathematical regression expressions in petroleum industry [8]. Genetic algorithm modeling differs from numerical modeling in the method of variables arrangement which is a genotype in the former, and phenotype in the later [52,53]. GEP first introduced by Ferreira [54] as a mathematical modification of GA. It resembles its predecessors; genetic algorithms (GA) and genetic programming (GP) in the selection of individuals populations according to fitness. The higher the fitness, the higher the probability of leaving more offspring, then introduces genetic variation. The main difference relies on individual's nature. In GA the individuals are symbolic strings of fixed length (chromosomes). In GP the individuals are non-linear moieties of different sizes and shapes (parse trees). In GEP the individuals are symbolic strings of fixed length(chromosomes) which are expressed as non-linear entities of different sizes and shapes capable of representing any expression tree [54,55]. To express GEP approach, an algebraic expression;

$$\frac{a*b}{c}+\sqrt{d-e} \qquad \text{(Equation 1)}$$

Can be represented as a genotype of GEP chromosomes as shown in Figure 2, Where (a, b, c, d, e) considered as terminals and (Q, /, *, -) expressed for the functions.

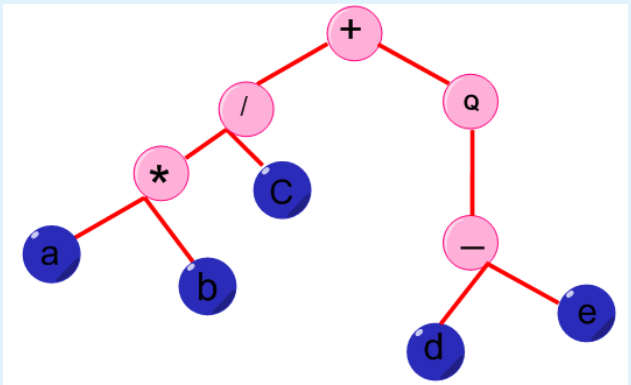


Figure 2: Two genotype GEP chromosomes.

Generally, regression analysis used to build up empirical correlations [14,56]. Regression analysis used to correlate a set of independent variables to predict one dependent variable. If only one independent variable isinvolved, it is known as a simple regression analysis whilemultiple regression analysis involvesmore than one independent variable [16]. General multiple regression models, which relates a dependent variable "y" to "k" predictor of independent variables, x_1, x_2, ..., x_k, is given by Equation 1 :

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots\ldots + \beta_k x_k$$

(Equation 2)

Where α and β's are regression analysis coefficients and expressed in matrix form as follow [16,57].

$$\begin{bmatrix} 1 & x_{11} & x_{12} & .. & x_{1n} \\ 1 & x_{21} & x_{22} & .. & x_{2n} \\ 1 & x_{31} & x_{32} & .. & x_{3n} \\ 1 & .. & .. & .. & .. \\ 1 & .. & .. & .. & .. \\ 1 & .. & .. & .. & .. \\ 1 & x_{nk1} & x_{nk2} & .. & x_{nkn} \end{bmatrix} \begin{bmatrix} \alpha \\ \beta_1 \\ \beta_2 \\ .. \\ .. \\ .. \\ \beta_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ .. \\ .. \\ .. \\ y_{nk} \end{bmatrix}$$

(Equation3)

Least-squares regression technique applied upon the nonlinear weighted values to minimize the sum-of-squared residuals between measured and simulated quantities [58]. The data fitted by a method of successive approximations [14,59]. The linearity or nonlinearity of the data pattern checked using scatter gram plotting. Since the precision of GEP models depends on different factors, so the number of genes and depth of expression tree increased. In this model development, we apply four genes including average percent relative error (ARE%), Average absolute percent relative error (AARE%),Standard deviation (S) and coefficient of determination (R^2) as a fitness functions (Figures 3-6), and a function set including (∗,+,–,ln, /) in order to develop the GEP-based model. The model correlated as a function of compositional analysis of hydrocarbon components (Z_{c1}-Z_{c7+}), physical properties of heptane plus fractions (C_{7+}) comprising molecular weight and specific gravity, the mole fraction of nonhydrocarbons (Z_{CO2}& Z_{N2}) and reservoir temperature. Physical properties and data range of 453 published data set used in model growth, as well as 27 datasets used in model validation, are reported in Table 2. The application range of this proposed formula to predict dewpoint pressure ranged from 1835.0 to 8553.0 psi. The optimum model for dewpoint prediction in this study is expressed as follow;

$$P_d = x^3 + y^3 \quad \text{(Equation 4)}$$

$$x = \frac{a_0 + a_1 Z_{C1} + a_2 Z_{C2} + a_3 Z_{C4} + a_4 (Z_{C4})^2 + a_5 Z_{C5} + a_6 Z_{C6} + (Z_{C7^+}) + a_7 T}{a_8 T + a_9} \quad \text{(Equation 5)}$$

$$y = \frac{b_0 + b_1 Z_{C1} (M_{C7^+}) + b_2 Z_{C3} + b_3 (Z_{C7^+}) + b_4 \ln(Z_{C7^+}) + b_5 Z_{CO2} + b_6 Z_{N2}}{b_7 (\gamma_{C7^+}) + b_8} \quad \text{(Equation 6)}$$

a_0=	30831054.885209	a_1=	25340412.798272	b_0=	36.805444	b_1=	0.036879

a_2=	17321431.646474	a_3=	55676491.863096	b_2=	-18.404394	b_3=	-27.417773
a_4=	-4992350.346216	a_5=	-4136106.206982	b_4=	1.070394	b_5=	-14.849297
a_6=	54245584.212136	a_7=	-54451.523407	b_6=	-6.962479	b_7=	-0.734094
a_8=	2545.141256	a_9=	-2571018.026613	b_8=	2.064002		

Parameters	Model development data (453)point			Model Validation data (27) point		
	Maximum	Minimum	Average	Maximum	Minimum	Average
Pd, psia	8553	1835	4615.691	5495	1139	3261.556
T res, F	313	40	204.2936	318	155	237.7689
ZC1, mole fr.	0.9604	0.2038	0.8003	0.9606	0.6185	0.8226
ZC2, mole fr.	0.1485	0.0021	0.0593	0.1239	0.0176	0.0635
ZC3, mole fr.	0.109	0.001	0.0314	0.0888	0.0082	0.0349
ZC4, mole fr.	0.0801	0.0012	0.0203	0.0329	0.0049	0.0166
ZC5, mole fr.	0.123	0.0013	0.0127	0.0124	0.0019	0.0068
ZC6, mole fr.	0.0871	0.001	0.0097	0.0211	0.0016	0.0069
ZC7+, mole fr.	0.1356	0.0027	0.0391	0.0819	0.0026	0.0201
ZCO2, mole fr.	0.5292	0	0.0156	0.1129	0.0002	0.0281
ZN2, mole fr.	0.434	0	0.0116	0.5355	0	0.0101
Specific gravity (γC7+)	0.8681	0.733	0.7866	0.8117	0.7758	0.7901
Molecular weight C7+ (g mol-1)	208	106	146.1082	168.9077	126.803	146.4725

Table 2: Summary of maximum, minimum and average data ranges used in model build up and validation.

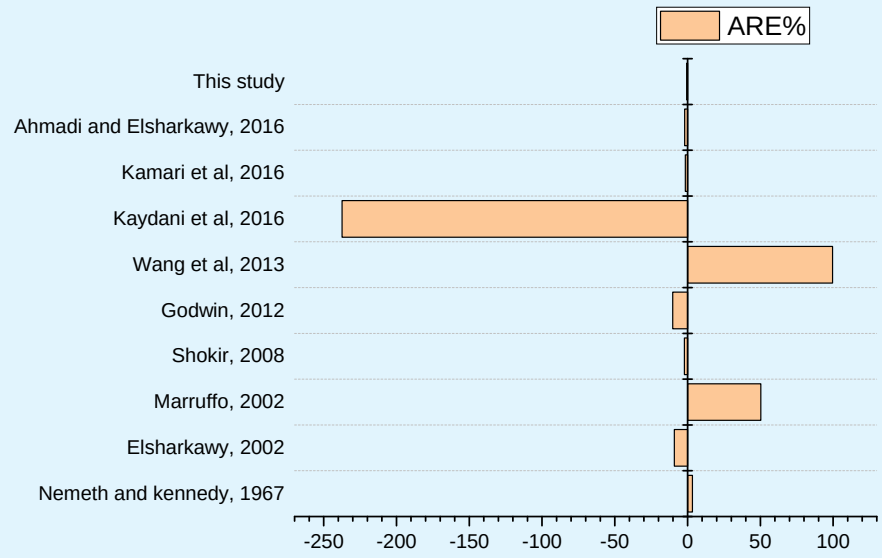


Figure 3: Performance of dew point correlations with respect to Average percent relative error.

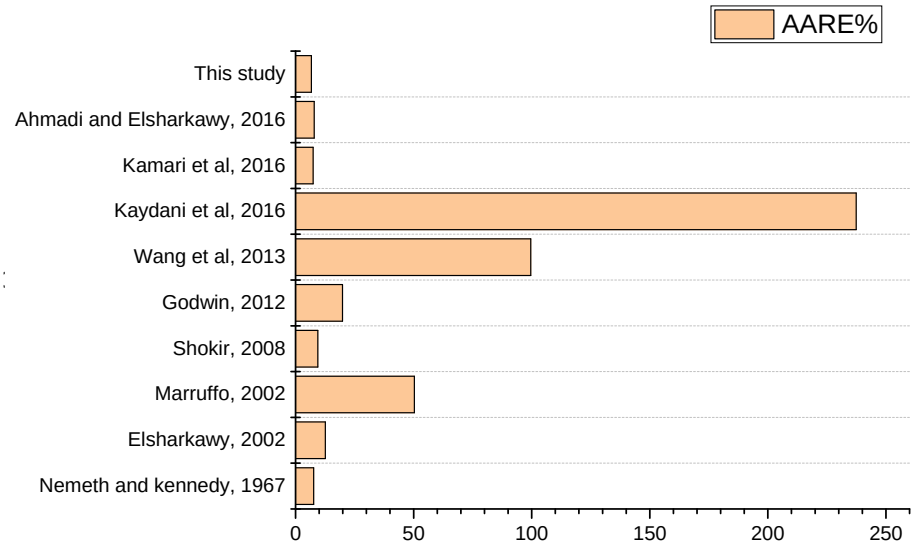


Figure 4: Performance of dew point correlations with respect to Average absolute percent relative error.

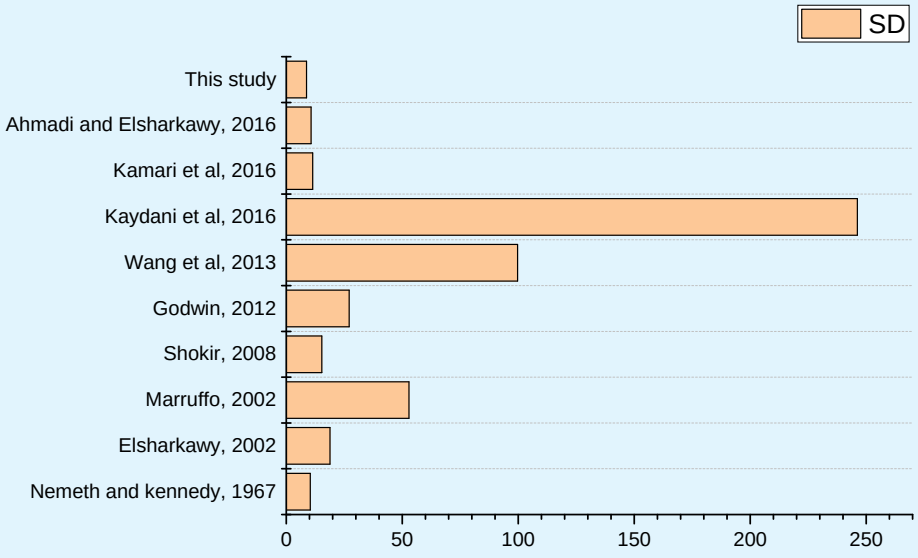


Figure 5: Performance of dew point correlations with respect to Standard deviation.

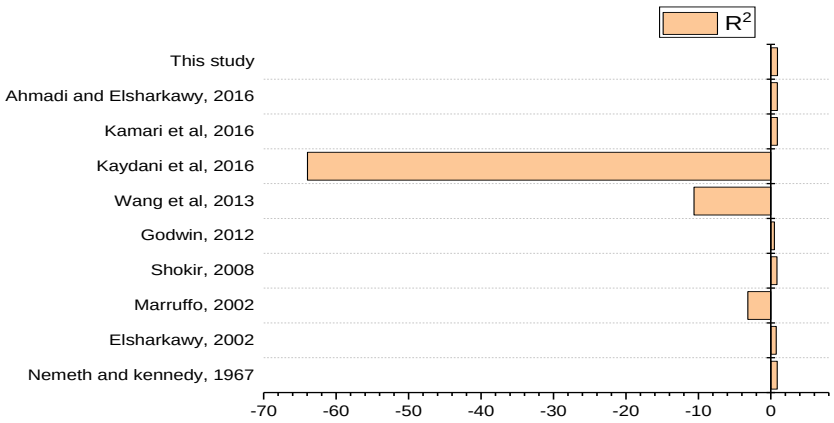


Figure 6: Performance of dew point correlations with respect to the coefficient of determination.

Results and Discussions

The accuracy and reliability of the developed correlation checked by statistical and graphical errors [16].

Statistical Error analysis

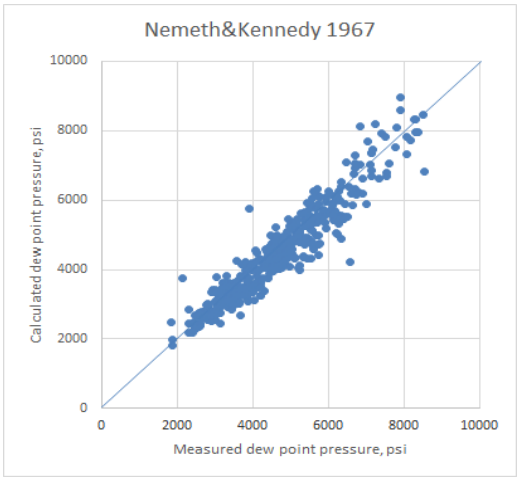
Accuracy and validity of the developed model were evaluated using the following statistical means; Average percent relative error (ARE%) [20,49], Average absolute percent relative error (AARE%) [60], Standard deviation (SD) [61] and coefficient of determination (R^2).The mathematical expression of each parameter reported in the literature [18]. Statistical errors of the published correlations and the developed one in this study are reported in Table 3. It is observed that the developed correlation has lower relative errors, lower root mean square error and lower standard deviation as compared to the published one, so it has more reliability to the measured values.

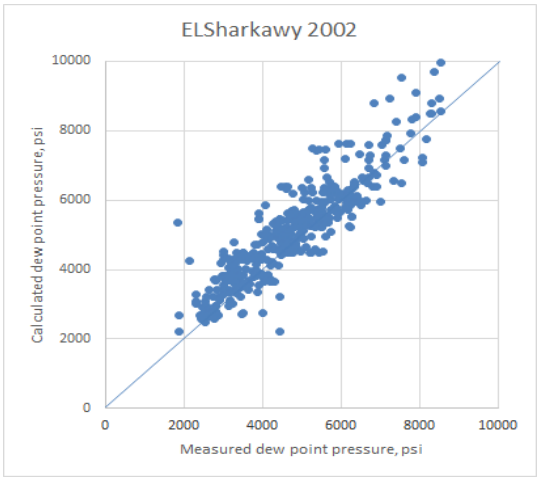
Correlation	ARE, %	AARE, %	SD	R^2
Nemeth and Kennedy, [33]	3.32	7.64	10.32	0.88
Elsharkawy, [41]	-9.07	12.58	18.86	0.75
Marruffo, [40]	50.3	50.3	52.9	-3.17
Shokir, [9]	-2.23	9.43	15.3	0.84
Godwin, [43]	-10.18	19.9	27.12	0.49
Wang et al, [44]	99.61	99.61	99.73	-10.6
Kaydani et al, [28]	-237.38	237.38	246.16	-63.96
Kamari et al, [8]	-1.55	7.41	11.36	0.89
Ahmadi and Elsharkawy,[32]	-1.97	7.9	10.67	0.9
This study	-0.6	6.72	8.75	0.92

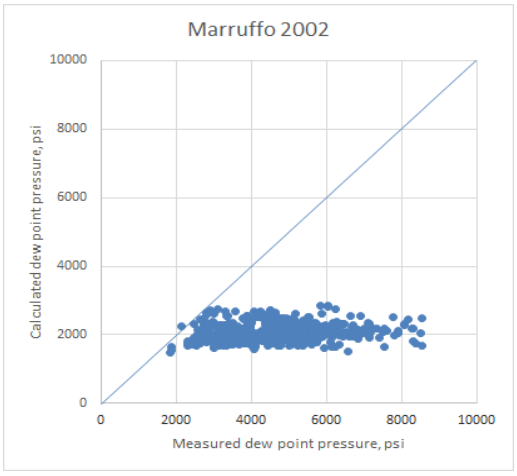
Table 3: Statistical accuracy of the published and developed correlations.

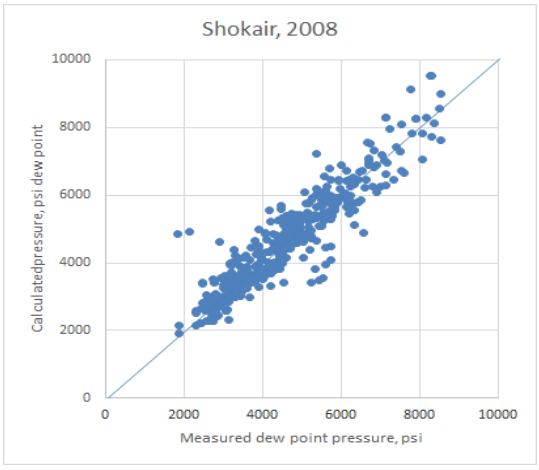
Graphical Error Analysis

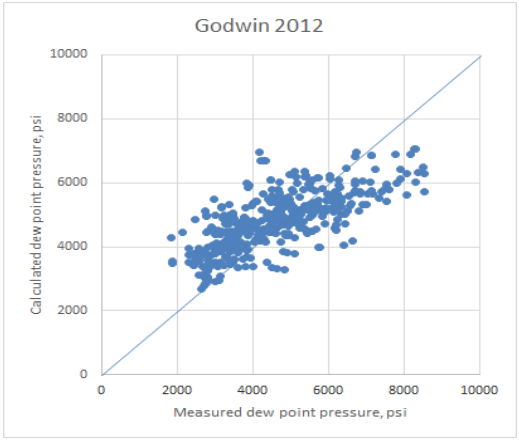
Graphical error analysis including cross plot technique was used in this study, where the predicted data are plotted against the measured one. Line with an angle of 45° degree is drawn through the predicted data, since the closer the plotted data to this line, the higher is the accuracy and prediction capability of the correlation [18]. Graphical plots of the published and developed correlations are reported in Figure 7.

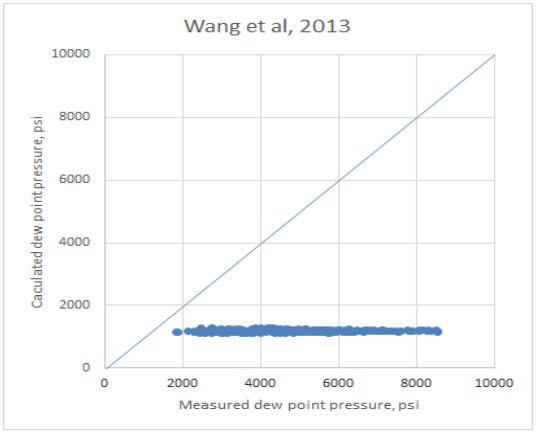












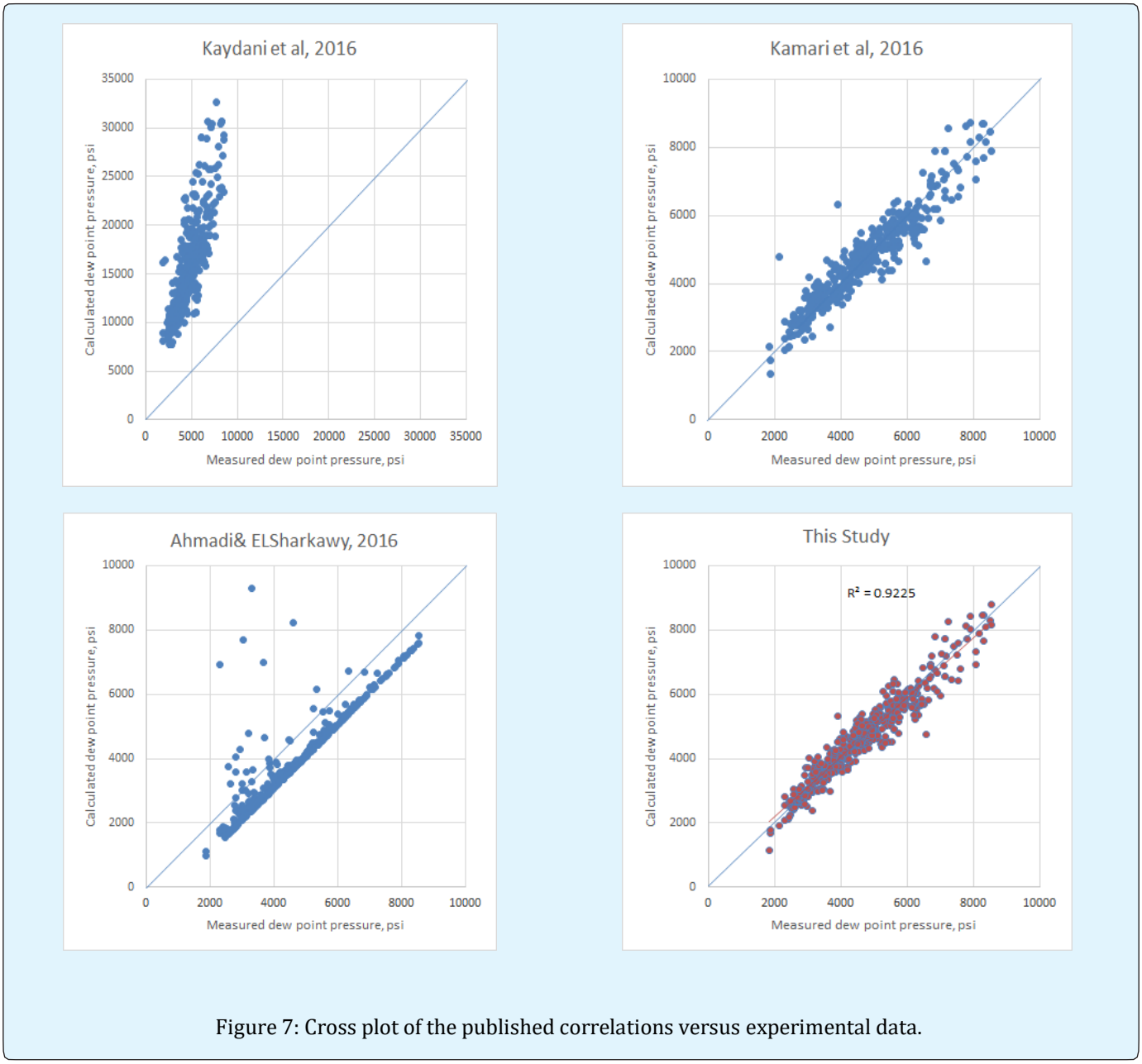


Figure 7: Cross plot of the published correlations versus experimental data.

The coefficient of determination (R^2) exhibits the strength of association between two variables, including the experimental and predicted data. The closer the R^2 to one, the closer the predicted values to the experimental data [18]. The cross plot indicates that the developed correlation has a higher coefficient of determination and correlation coefficient (R^2= 0.9225 & r=0.9604) than the published relations, so it is expected that it has high accuracy. Figure 8 reveals a great compliance between the measured and calculated data, which indicate high reproducibility of the proposed relation.

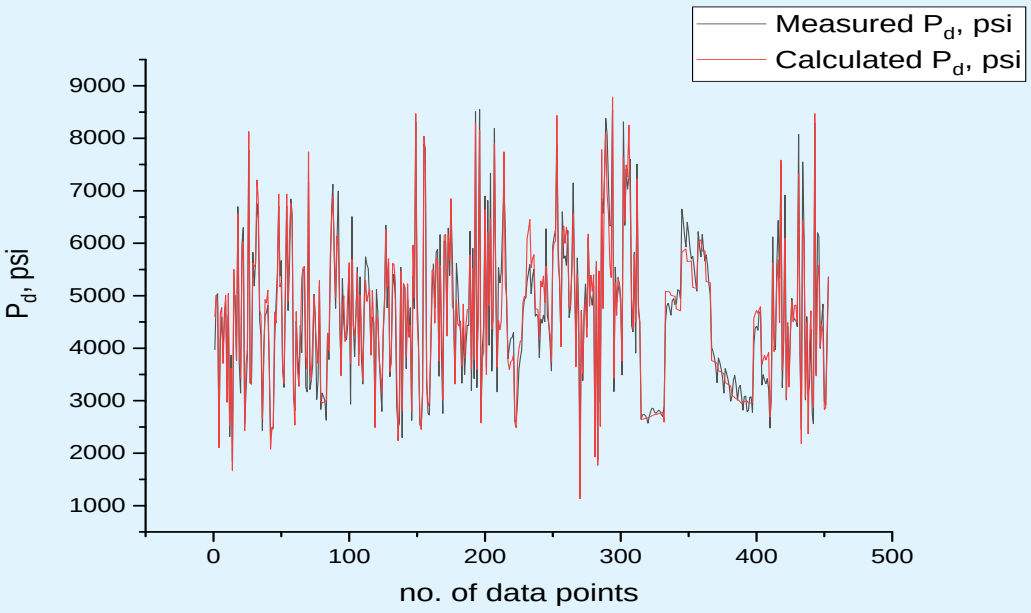


Figure 8: Comparison between experimental and calculated dew point pressure.

Validation of Correlation

Validity and applicability of thedeveloped empirical correlations carried out through graphical and statistical error analysis using 27 data sets not used in the correlation development. Figure 9 shows the cross plot of the measured and predicted data. We can observe that the coefficient of determination reach (R^2= 0.9451) which indicates a high accuracy of this correlation related to samples validation. Also, the statistical analyses show low relative error percentage, low standard deviation and high coefficient of determination. (ARE%= -1.0771, AARE%= 6.9707, and SD= 0.0888).

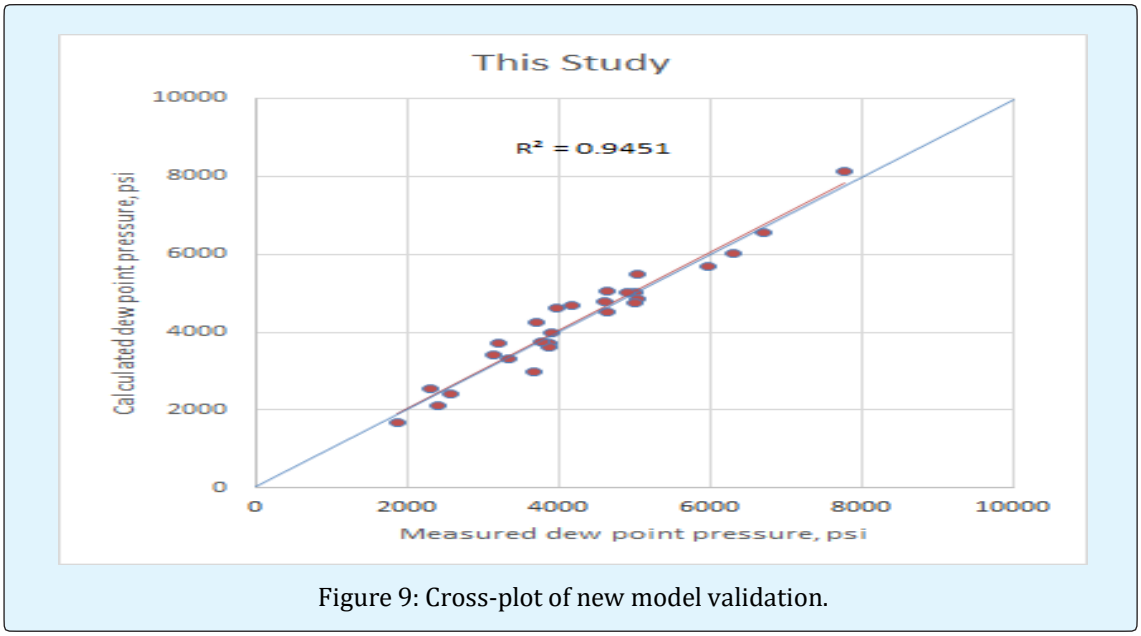


Figure 9: Cross-plot of new model validation.

Conclusion

A novel model with precise estimation of dewpoint pressure in retrograde gas condensate reservoirs was developed depending on 453 dataset as function of mole fraction of (Z_{C1}-Z_{C7^+}), physical properties of heptane plus fractions (C_{7^+}) including molecular weight and specific gravity, mole fraction of nonhydrocarbons (Z_{CO2} & Z_{N^2}) and reservoir temperature using a combination of gene expression programming (GEP) and multiple regression analysis. Experimental PVT analysis carried out to measure dewpoint pressure of the samples used in model validation in addition to compositional analysis. Comparative evaluation of the developed model and the well-known published correlations from the literature carried out using statistical and graphical error analyses. The obtained results indicate that, the developed correlation exhibit great accuracy and reproducibility with a coefficient of determination (R^2= 0.9225) and lower relative errors (ARE%= -0.6, AARE%= 6.72). Model validation carried out on 27 gas condensate samples through graphical and statistical error analysis where the coefficient of determination reach (R^2= 0.9451) which indicates a high reliability of the proposed correlation.

Nomenclature

P_d	Dewpoint pressure, psi
GEP	Gene expression programming
PVT	Pressure-volume-temperature
CCE	Constant composition expansion
GA	Genetic Algorithm
T_c	Critical temperature
T_{ct}	Cricondentherm temperature
LDO	liquid drop out
CVD	Constant volume depletion
GOR	Gas-oil ratio
API	Oil gravity
GA	Genetic algorithm
γ_{C7^+}	The specific gravity of heptane plus components
M_{C7^+}	The molecular weight of heptane plus components (g mol^{-1})
Z_{C1}-Z_{C7+}	The mole fraction of hydrocarbon components from methane to heptane plus components
Z_{CO2}	The mole fraction of CO_2
Z_{N2}	The mole fraction of N_2
T	Reservoir temperature, °F
ARE%	Average percent relative error
AARE%	Average absolute percent relative error
SD	Standard deviation
r	Correlation coefficient
R^2	Coefficient of determination

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