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Assessment and Development of Inflow Performance Relationship of Gas reservoirs

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Abstract: The Inflow Performance relationship (a Cartesian plot of bottom-hole flowing pressure versus surface flow rate) is considered one of the diagnostic tools used by petroleum engineers to evaluate the performance of a flowing well. The plot is used to determine whether any well under consideration is performing as expected or not. If it is not, then remedial action may be necessary. The equation that describes this curve is the Inflow Performance Relationship. This equation can be determined both theoretically and empirically. This study presents both conventional methods and artificial intelligence techniques for predicting inflow performance relationship for a dry gas reservoir. The data used in this study was collected from conventional PVT reports for a Yemeni dry gas reservoir. Statistical analysis was performed to see which of these methods are more reliable and accurate method for predicting the inflow performance relationship for the dry gas reservoir. Pseudo pressure approach is the lowest Average Absolute Relative Error (AARE) of all the three conventional methods with AARE (13.282%). The artificial intelligence techniques provide better estimation of the inflow performance relationship than conventional methods with average absolute relative error 0.029% and 0.0001% for artificial neural network and fuzzy logic respectively.

Keywords: Inflow performance relationship, developed new model, Yemeni dry gas reservoirs, artificial intelligence.

I. INTRODUCTION

Well performance is a term describes fluid droplet journey from reservoir to gas-oil separator passing through tubing and pipelines. Outflow Performance Relationship (OPR) and Inflow Performance Relationship (IPR) are two mathematical tools used together to predict with the well performance. The OPR depicts pressure drop that should be loosed when the fluid flow through tubing and pipeline into gas-oil separator while IPR is a correlation reflects reservoir ability to supply production well with fluid.

Artificial Intelligence (AI) techniques has become very common in most of petroleum engineering application recently, for example, drilling engineering, reservoir engineering, production engineering, petrophysics, rock mechanics and exploration [1-4].

This study covered both conventional methods and artificial intelligence techniques for estimating inflow performance relationship of gas and oil reservoirs. The objectives of this work are:

- Determination of inflow performance relationship of gas reservoir using conventional methods such as P-approach, P^2-approch and pseudo pressure approach (*m (p)*).
- To compare the performance and accuracy of IPR gas conventional equations, statistical error analysis is performed. The statistical parameters used for comparison are average absolute percent relative error, standard deviation and correlation coefficient.
- Determination of inflow performance relationship using Artificial intelligence techniques such as artificial neural network and fuzzy logic.

II. GENERAL OVERVIEW

Well Deliverability:

All well deliverability equations describe the relationship between the well production rate and the drawdown pressure, i.e. the difference between the reservoir pressure and the flowing bottom hole pressure. Presenting the production rate as a function of the drawdown pressure helps in comparing wells as well as in estimating the production rate under various conditions. This is also known as the "inflow performance relationship" or IPR [5].

Gas Well Deliverability:

In a single-layered gas reservoir, the gas well deliverability can be approximated using a pseudo-steady state relationship developed from Darcy's law

$$m(\overline{\mathrm{P}}) - \mathrm{m(Pwf)} = \frac{1424qT}{kh}\left[\ln\left(\frac{0.472\ re}{rw}\right) + S + Dq\right] \quad (1)$$

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Which can be rearranged as:

$$m(\overline{\text{P}}) - \text{m(Pwf)} = \frac{1424qT}{kh}\left[\ln\left(\frac{0.472\ re}{rw}\right) + S\right]q + \frac{1424TD}{kh}\ q^2 \tag{2}$$

Alternatively:

$$m(\overline{\text{P}}) - \text{m(Pwf)} = aq + bq^2 \tag{3}$$

Where: -

$$a = \frac{1424qT}{kh}\left[\ln\left(\frac{0.472\ re}{rw}\right) + S\right] \tag{4}$$

$$b = \frac{1424TD}{kh} \tag{5}$$

The Dq term refer to the turbulence skin effect, which could be quite high for some high rate wells. Several authors proposed approximations for the non-Darcy coefficient (D), one of them is the following empirical correlation:

$$D = \frac{2.715 \times 10^{-12}\beta MPsc}{h\mu g(Pwf)rwTsc} \tag{6}$$

$$\beta = 1.88 * \ 10^{10}K^{-1.47}\emptyset^{-0.53} \tag{7}$$

It was found that much simpler equation evolving the pressure square rather than the pseudo-pressure could obtain almost the same results as follows:

$$\overline{\text{P}}^2 - P_{wf}{}^2 = \frac{1424\bar{\mu}\,\bar{z}\,Tq}{kh}\left[ln\left(0.472\frac{r_e}{r_w}\right) + S + Dq\right] \tag{8}$$

Which can be rearranged as:

$$\overline{\text{P}}^2 - P_{wf}{}^2 = \frac{1424\bar{\mu}\,\bar{z}\,T}{kh}\left[ln\left(0.472\frac{r_e}{r_w}\right) + S\right]q + \frac{1424\bar{\mu}\,\bar{z}\,TD}{kh}q^2 \tag{9}$$

Alternatively:

$$\overline{\text{P}}^2 - P_{wf}{}^2 = aq + bq^2 \tag{10}$$

Where:

$$a = \frac{1424\bar{\mu}\,\bar{z}\,T}{kh}\left[ln\left(0.472\frac{r_e}{r_w}\right) + S\right] \tag{11}$$

$$b = \frac{1424\bar{\mu}\,\bar{z}\,TD}{kh} \tag{12}$$

In addition, the gas well deliverability can be approximated using pressure approach as follows:

$$\overline{\text{P}} - P_{wf} = \frac{141.2 \times 10^3 B_g\,\bar{\mu}\,q}{kh}\left[ln\left(\frac{0.472r_e}{r_w}\right) + S + Dq\right] \tag{13}$$

Which can be rearranged as:

$$\overline{\text{P}} - P_{wf} = \frac{141.2 \times 10^3 B_g\,\bar{\mu}}{kh}\left[ln\left(\frac{0.472r_e}{r_w}\right) + S\right]\text{q} + \frac{141.2 \times 10^3 B_g\,\bar{\mu}\,D}{kh}q^2 \tag{14}$$

Alternatively:

$$\overline{\text{P}} - P_{wf} = aq + bq^2 \tag{15}$$

Where:

$$a = \frac{141.2 \times 10^3 B_g\,\bar{\mu}}{kh}\left[ln\left(\frac{0.472r_e}{r_w}\right) + S\right] \tag{16}$$

$$b = \frac{141.2 \times 10^3 B_g\,\bar{\mu}D}{kh} \tag{17}$$

Artificial Intelligence (AI): It is defined as “the subfield of computer science concerned with the use of computers in tasks that are normally considered to require knowledge, perception, reasoning, learning, understanding and similar cognitive abilities” [6]. It uses soft computing techniques to provide better results than the conventional solutions. It includes, amongst many things, perceptrons, problem solving, language, conscious, and unconscious processes. Artificial Intelligence has become increasingly popular in the last two decades in the petroleum industry. It has been extensively used and many SPE papers show successful usages of AI methods to solve petroleum engineering problems [7]· AI applications in the petroleum industry includes lithofacies identification, PVT properties estimation, production optimization, reserve estimation, history matching, Measuring While Drilling (MWD) data analysis, drill bit diagnosis, hydraulic fracture analysis, bottom hole pressure prediction, well test analysis, critical gas flow rate prediction, and gas-lift optimization [8-9]

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Artificial Intelligence Methods:

A. Artificial Neural Network (ANN)

An ANN model is a computer model that attempts to mimic simple biological learning processes and simulate specific functions based on the working of the human nervous system. It is an adaptive, parallel information processing system, which is able to develop associations, transformations or mappings between objects or data. The fundamental building block for neural networks is the single-input neuron as shown in Fig. 1. In addition, the simple neuron can be extended to handle inputs that are vectors. A neuron with a single R-element input vector is shown in Fig. 2.

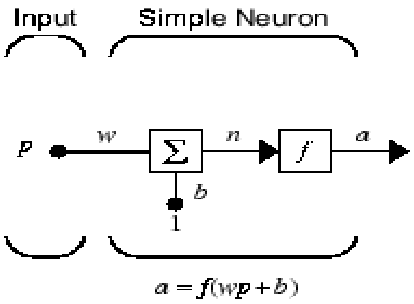

Fig.1 single-input neuron [10]

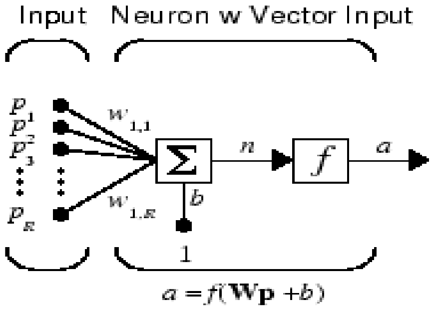

Fig. 2 Vectors-inputs neuron [10]

Three distinct functional operations take place in this example neuron. First, the scalar input (P) is multiplied by the scalar weight (W) to form the product (WP), again (a) scalar. Second, the weighted input (WP) is added to the scalar bias (b) to form the net input n. In this case, the bias can be viewed as shifting the function (*f*) to the left by an amount b. The bias is much like a weight, except that it has a constant input of 1. Finally, the net input is passed through the transfer function (*f*), which produces the scalar output (a). The names given to these three functions are: the weight function, the net input function and the transfer function. Many transfer functions are included in the Neural Network Toolbox software. Two of the most commonly used functions are shown below. Log-sigmoid transfer function generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity as shown in Fig. 3. While linear output neurons are used for function fitting problems. The linear transfer function purelin is shown in Fig. 4.

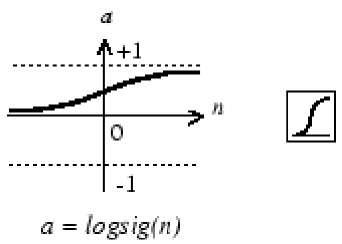

Fig. 3 Log-sigmoid transfer function [10]

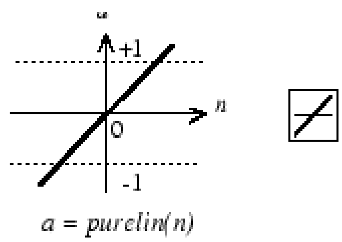

Fig. 4 Linear transfer function [10]

Back propagation network (BPN) often has one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear relationships between input and output vectors. The linear output layer is most often used for function fitting (or nonlinear regression) problems. Fig. 5 shows back propagation network with sigmoid and linear transfer functions.

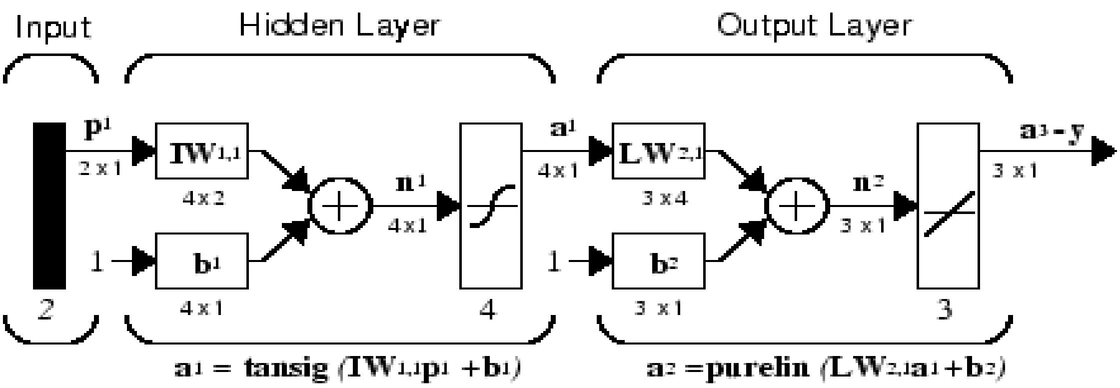

Fig. 5 Architecture of back propagation network [10]

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B. Fuzzy Logic Technique

Fuzzy logic model has two different meanings. In a narrow sense, fuzzy logic is a logical system, which is an extension of multivalued logic. However, in a wider sense fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory that relates to classes of objects with unsharp boundaries in which membership is a matter of degree. The point of fuzzy logic is to map an input space to an output space, and the primary mechanism for doing this is a list of if-then statements called rules. All rules are evaluated in parallel, and the order of the rules is unimportant. The rules themselves are useful because they refer to variables and the adjectives that describe those variables. You have to define your system like rule base, membership functions and their number and shape manually. A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse, a fancy name for a simple concept. There are different kinds of membership functions for example, triangular membership function (trimf), trapezoidal membership function (trapmf), Gaussian membership function (gaussmf and gauss2mf), and generalized bell membership function(gbellmf) as shown in Fig. 6 and Fig. 7.

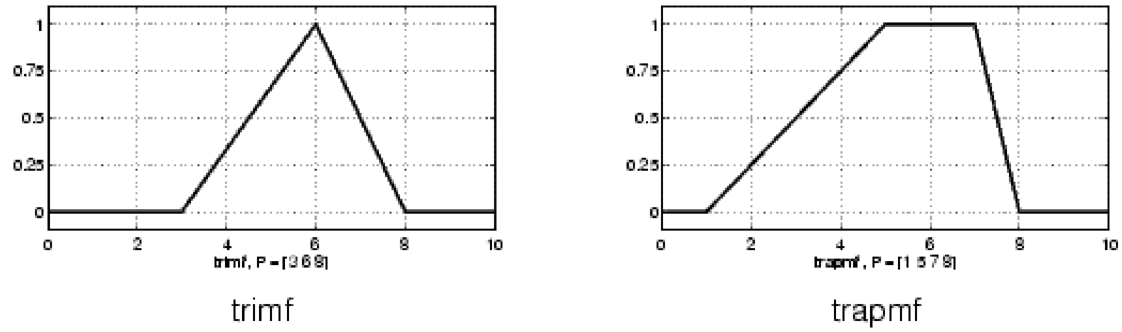

Fig. 6 Triangular and trapezoidal membership functions [11]

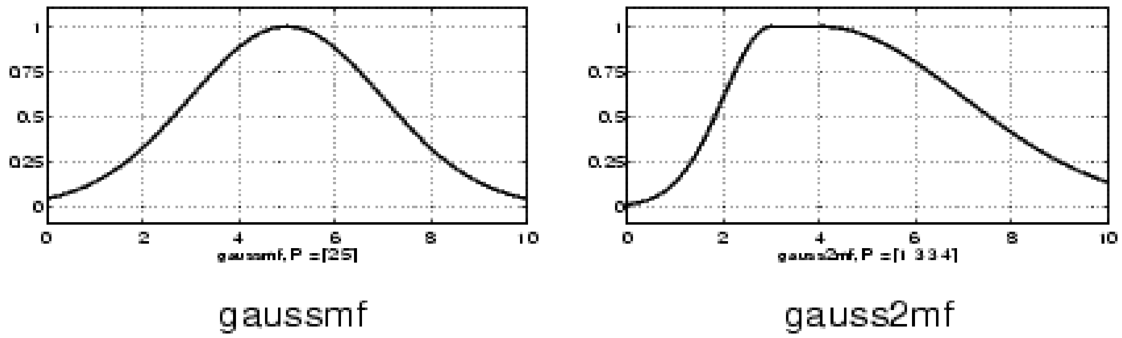

Fig. 7 Gaussian membership functions [11]

III. RESEARCH METHODOLOGY

A. Data Description

A huge data sets used for this work were collected from conventional PVT reports for a Yemeni dry gas reservoir. Each data set contains gas flow rate, bottom hole flowing pressure, gas viscosity, gas compressibility factor. Statistical distributions such as maximum, minimum, mean, range, mid-range and standard deviation of the input data are shown in Table 1. As can be seen from Table 1 gas flow rate of the data ranged between 12MSCF/D to 5528 MSCF/D. For bottom hole flowing pressure, the data ranged between 15 psia to 5991 psia. Gas viscosity ranged from 0.009 cp 0.035 cp. For gas compressibility factor, the data ranged between 0.745 to 0.999. The average reservoir temperature is 180˚ F. Reservoir permeability is 0.15 md, reservoir drainage radius and reservoir thickness are 1400 ft and 80 ft, respectively.

TABLE 1 STATISTICAL DISTRIBUTIONS OF THE INPUT DATA FOR DRY GAS RESERVOIR

Property	Min	Max	Range	Mid-Ran.	Mean	Std
q	12	5528	5516	2770	3325.747	1676.5
pwf	15	5991	5976	3003	3003.074	1729
μ_g	0.009	0.035	0.026	0.022	0.0217	0.008
Z	0.745	0.999	0.255	0.872	0.8555	0.088

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B. Evaluation Criteria

To achieve this work, MATLAB statistical error analysis and MATLAB cross plot error analysis were used to compare the performance and accuracy of IPR gas conventional equations. In addition, this study presents both Artificial Neural Networks and fuzzy logic techniques for predicting the well performance of dry gas reservoirs. The statistical parameters used for comparison are average absolute percent relative error, standard deviation and correlation coefficient. Equations for those parameters are given below:

1. Average Absolute Percent Relative Error

$$E_{aa} = \frac{1}{n} \times \sum_i^n [E_i] \tag{18}$$

Where E_i is the relative deviation of an estimated value from an experimental value

$$E_i = \left[\frac{V_{exp} - V_{est}}{V_{exp}}\right] \times 100, i = 1,2,3 \dots \dots \dots n \tag{19}$$

The value of E_i can be positive or negative; the sing gives an indication about the estimated value either bigger or smaller than the actual value. The lower absolute value of E_i means the high accuracy estimated value of the model.

2. Standard deviation

$$E_{std} = \frac{1}{n-1} \sum_{i=1}^n [(E_i - \bar{E})^2]^{\frac{1}{2}} \tag{20}$$

Where:

$$\bar{E} = \frac{1}{n} \sum_{i=1}^n E_i \tag{21}$$

3. The Correlation coefficient (CC)

$$R = \sqrt{1 - \sum_{i=1}^n \frac{[V_{exp} - V_{est}]}{\sum_{i=1}^n [V_{exp} - \bar{V}]}} \tag{22}$$

$$\bar{V} = \frac{1}{n} \times \sum_i^n [V_{exp}] \tag{23}$$

The CC measures the statistical correlation between the predicted and actual values. A value of "1" means perfect statistical correlation and a "0" means there is no correlation at all.

Firstly, three main conventional methods (P-approach, P^2-approach and pseudo pressure approach (*m (p)*)) were used to determine the inflow performance relationship of this dry gas reservoir. Then comparison the performance and accuracy of the three conventional methods and statistical error analysis were performed. Secondly, Artificial Intelligence technology was used to predict inflow performance relationship of this dry gas reservoir. Firstly, 70% of the data points were used to train the AI models while the remaining 30% were used for validating and testing the models. Then results were compared with those of the conventional methods.

Configuration of the ANN Model

The inputs of the model were wellbore pressure in (psi) and gas viscosity in (cp) and gas compressibility factor(z), whereas the output was gas flow rate in (MSCF/D). In this part, Artificial Neural Network was used to predict the inflow performance relationship of the gas reservoir. It is to be noted here that the points that were selected for training and testing were randomized. This helps to guarantee that the data used for training the model covers all possible ranges of the dataset.

Configuration of the FL Model

Fuzzy Logic was used in this part for predicting the inflow performance relationship based on the wellbore pressure in (psi) and gas viscosity in (cp) and gas compressibility factor(z) as inputs of the model. 70% of the data points were used to train the FL model while the remaining 30% was used for validation and test. In order to establish a valid evaluation of FL results, we have used the same criteria for evaluation FL performance; average absolute percent relative error, standard deviation and correlation coefficient.

IV. RESULTS AND DISCUSSION

The results obtained by conventional methods showed that the best conventional method for this dry gas reservoir is pseudo pressure m(P) method with average absolute percent relative error (13.282%), whereas P- approach gave us very

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high average absolute percent relative error (89.908%) and P^2-approch gave us result with (22.288%) average absolute percent relative error. Fig. 8 through Fig. 10 show the plots of predicted versus measured gas flow rate values for the three main conventional methods (P-approach, P^2-approach and pseudo pressure approach (*m (p)*)), respectively.
The results obtained by artificial intelligence techniques showed better results than conventional methods with average absolute percent relative error of ANN (0.029337%) and only (0.000134%) average absolute percent relative error for Fuzzy logic. Artificial neural network error distribution as shown in Fig. 11 illustrates that most of the points are located on the zero horizontal line which means this method give us good estimation for gas flow rate. While Fig. 12 through Fig. 13 show the plots of estimated versus measured gas flow rate values for training and testing, respectively using FL method. Fig. 14 through Fig. 15 illustrate the plots of calculated versus measured gas flow rate for ANN and FL respectively. Whereas Fig. 16 shows the plots of calculated versus measured gas flow rate values for conventional methods and AI techniques.

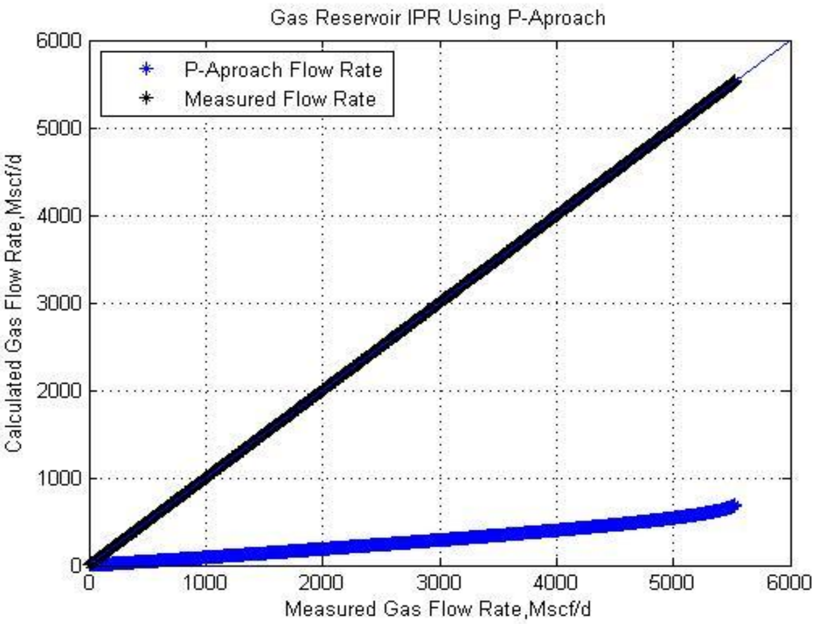

Fig. 8 Gas reservoir IPR correlation using P-approach

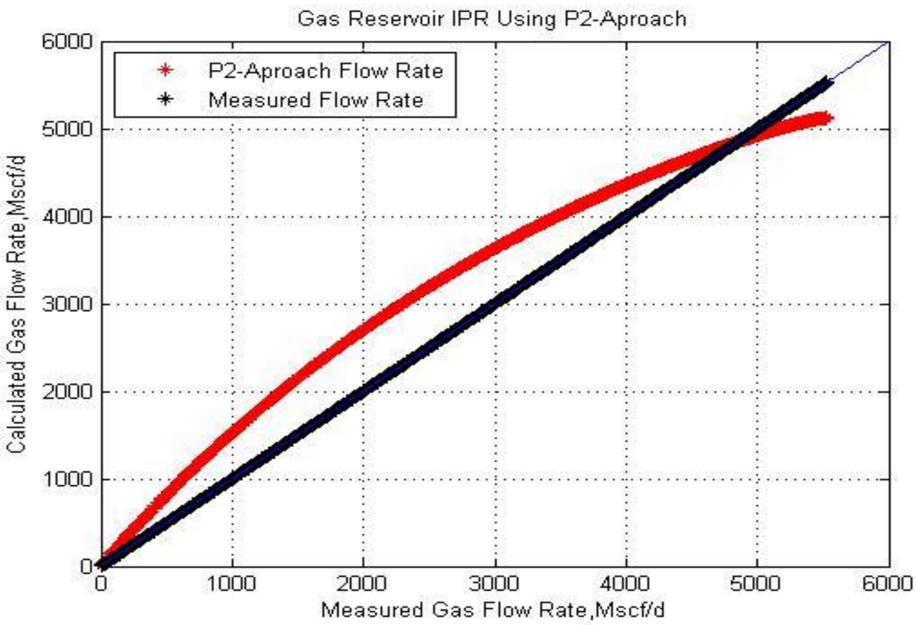

Fig. 9 Gas reservoir IPR correlation using P^2-approach

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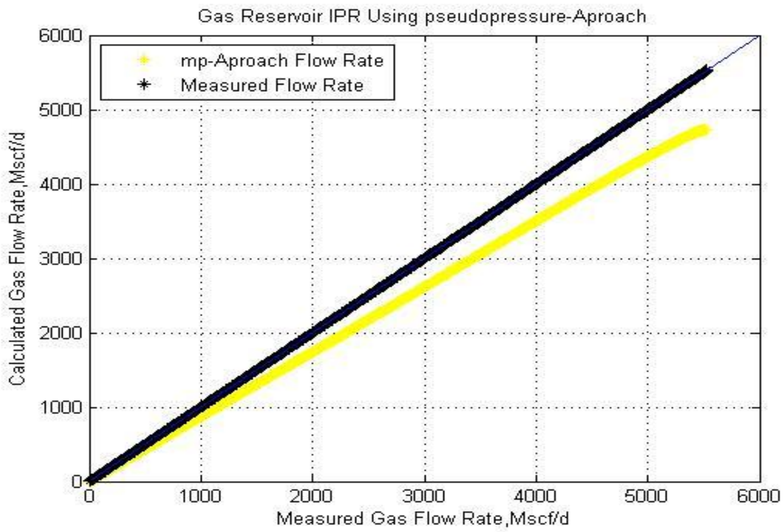

Fig. 10 Gas reservoir IPR correlation using pesudo pressure approach

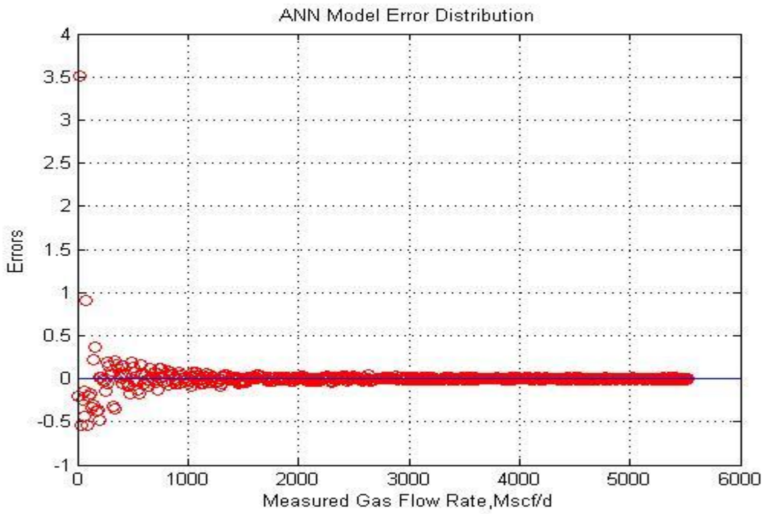

Fig. 11 ANN Model Error Distribution

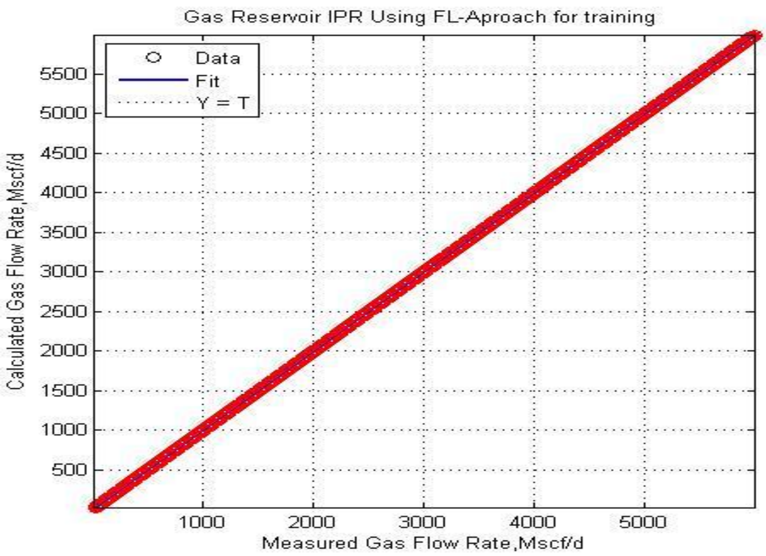

Fig. 12 Gas reservoir IPR correlation using FL for training

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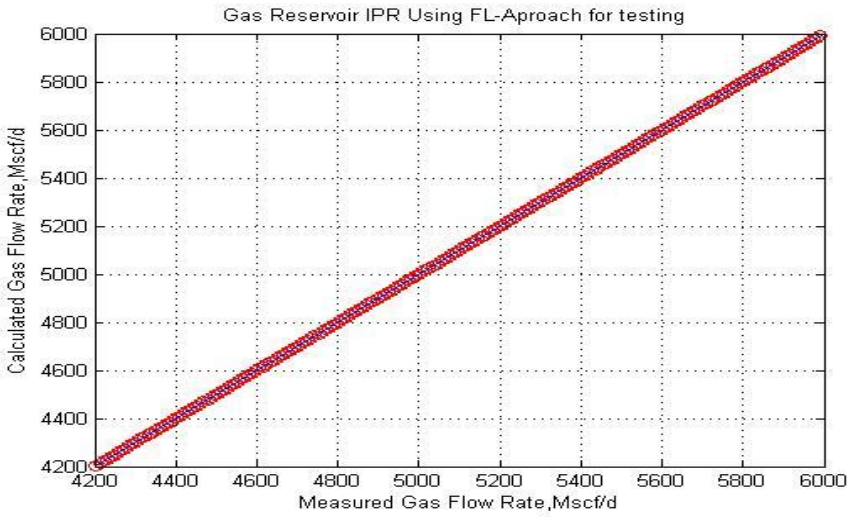

Fig. 13 Gas reservoir IPR correlation using FL for testing

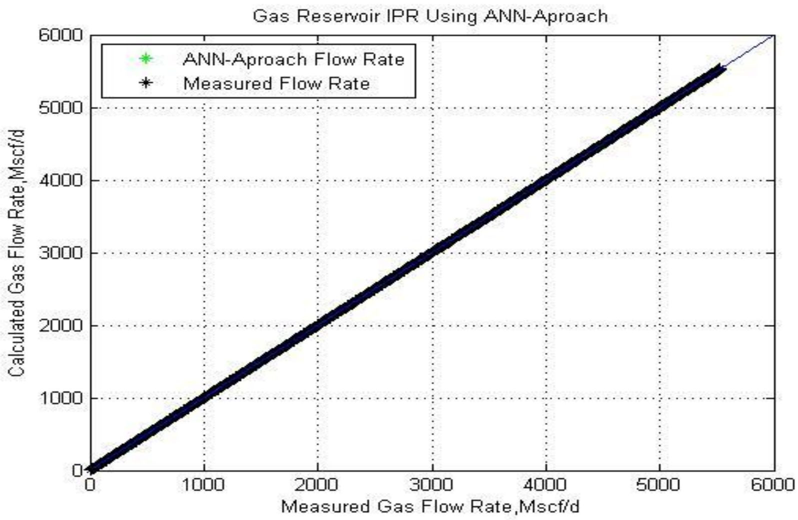

Fig. 14 Gas reservoir IPR correlation using ANN approach

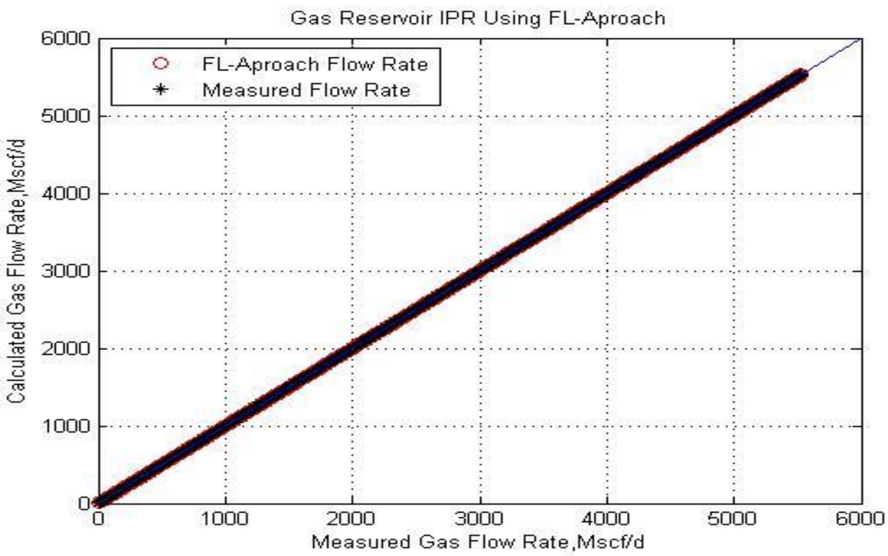

Fig. 15 Gas reservoir IPR correlation using FL approach

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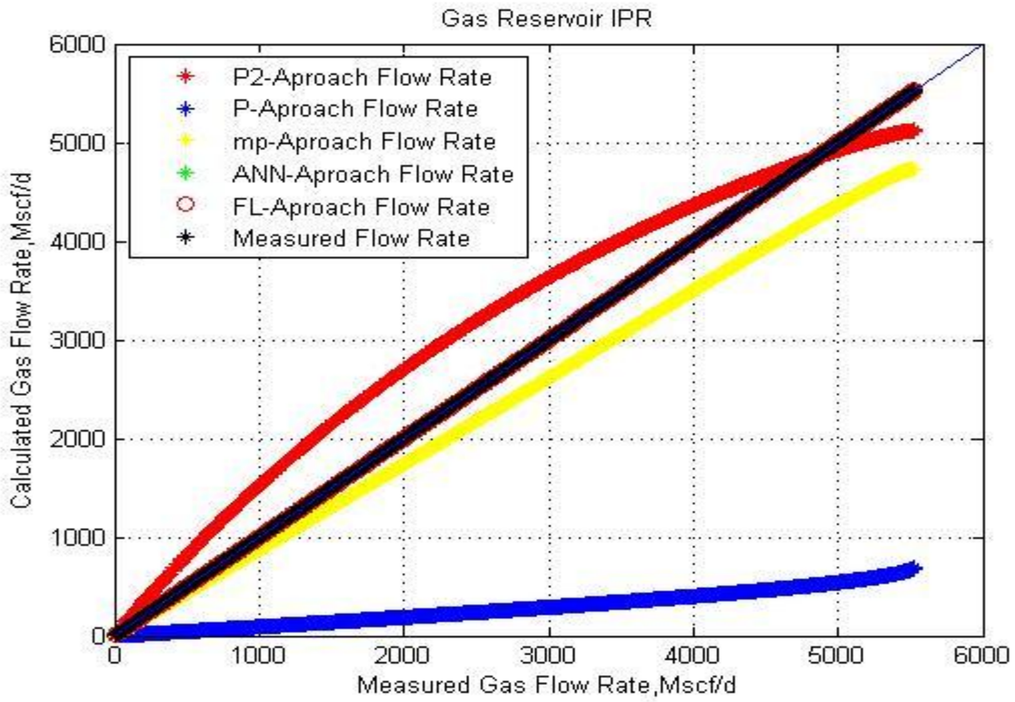

Fig. 16 Gas reservoir IPR correlation using conventional and AI methods

A summary of statistical error analysis for both conventional methods and artificial intelligence techniques can be clearly observed in Table 2.

TABLE 2 STATISTICAL ERROR ANALYSIS

	Conventional methods			Artificial Intelligence techniques	
Method	P-Approach	P^2 – Approach	m(P)- Approach	ANN Model	FL Model
AARE	89.908	22.288	13.282	0.029	0.0001
Std	35.918	23.368	4.323	0.151	0.0001
R	0.991	0.984	0.999	1	1

Fig. 17 shows the plot of bottom hole flowing pressure in (psia) versus gas flow rate in (MSCF/D) using both conventional and artificial intelligence methods. As can be clearly observed from this figure, artificial intelligence methods have the lowest average absolute percent relative error and the lowest standard deviation of this dry gas reservoir IPR. Whereas pseudo pressure approach is considered the lowest average absolute percent relative error and the lowest standard deviation of all the three conventional methods.

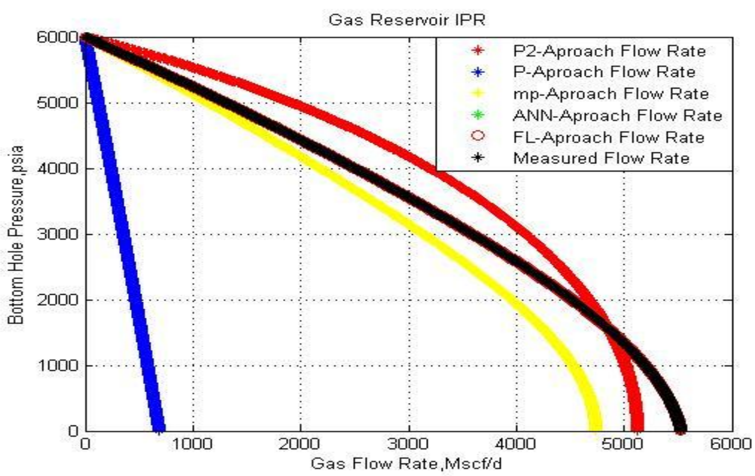

Fig. 17 IPR of gas reservoir using conventional and AI methods

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V. CONCLUSIONS

Based on the analysis of the results obtained in this study, the following conclusions can be made: -

1- Pseudo pressure approach is the lowest AARE of the conventional methods with AARE (13.282%). While P-approach is the highest AARE (89.908%) and and P^2-approch with AARE (22.288%).
2- The results show that the artificial intelligence techniques provides better predictions and higher accuracy of the IPR than conventional methods. The FL model provides prediction of the IPR with AARE only 0.0001% and ANN model gave result with AARE of 0.029%.

Nomenclature:

IPR = inflow performance relationship
ANN = Artificial neural network
FL = Fuzzy logic technique
Eaa = Average absolute percent relative error
Estd = Standard deviation error
R = Crrelation coefficient
V_{exp} = Experiment (Measured) value
V_{est} = Estimated value

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