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Neural Network Prediction of Inflow Performance Relationship of Producing Wells- Yemeni Oil Field

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Abstract

The inflow performance relationship (IPR) characterizes the way of behaving of the flowing pressure of oil well and the production flow rate, that is a key tool for understanding the reservoir and the well way of behaving and quantifying the production flow rate. The inflow performance relationship is oftentimes needed for design the completion of the well, production optimization of the well, analysis of the nodal determinations, and artificial lift design. Today, various inflow performance relationship correlations subsist in the industry of petroleum, as well as some analytical equations, that generally pain from bound applicability due to high absolute error. In this paper the most correlations were evaluated for prediction IPR for Yemeni oil fields, evaluation between different other correlations. This study presents an analytical method for improved oil flow rate for Yemeni oil wells employing machine learning using input production parameters. New Artificial Neural Networks model was examined by real Yemeni data and gives the best results are obtained from new model and based on the results obtained with AAPE of 0.98 %, R^2 of 0.9997 and Standard Deviation of 0.85 compared with AAPE of 8.6 % , R^2 of 0.996 and Standard Deviation of 3.55 for Khadafy. A M et al. model which is the best correlation exist, it is recommended to use the developed model to predict IPR. The developed model will be of significant assistance to petroleum industry operators in the Yemeni oil for quick effective estimates of oil flow rates.

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Keywords

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1. Introduction

The inflow performance relationship (IPR) characterizes the way of behaving of the flowing pressure of the well and production flow rate, that is a main device in comprehension the reservoir and the well way of behaving and quantifying the production flow rate. The design of well completion, nodal analysis calculations, optimizing well production and artificial lift design is required the IPR. There are two methods for prediction Inflow Performance Relationship they are:

1) Determine IPR through flow test: this way consider time dependent and limited by the cost.

2) Determine IPR from correlations. There are several correlations to determine IPR such as Vogel, Fetkovich, standing, etc. those methods is data field independent and limited by highest error.

So there is need to determine the IPR for oil wells with high accuracy for Yemeni oil fields. in this project the new Artificial Neural Network model for calculating IPR for Yemeni oil fields is developed. The new model outperforms empirical correlations.

Today, various inflow correlations subsist in the industry of petroleum [5, 9, 12, 16, 18, 31, 32, 33] which are presented in TABLE 1.

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Table1 Summary of IPR Correlations [5]

Authors	Correlation
Vogel (1968)	$$\frac{q_o}{q_{o,max}} = 1 - 0.2\left[\frac{p_{wf}}{p_r}\right] - 0.8\left[\frac{p_{wf}}{p_r}\right]^2$$
Fetkovitch (1973)	$$\frac{q_o}{q_{o,max}} = \left[1 - \frac{{p_{wf}}^2}{{p_r}^2}\right]^n$$
Klins and Majher (1992)	$$\frac{q_o}{q_{o,max}} = 1 - 0.295\left[\frac{p_{wf}}{p_r}\right] - 0.705\left[\frac{p_{wf}}{p_r}\right]^N$$ Where:$N = \left[0.28 + 0.72\left(\frac{p_r}{p_b}\right)\right] * (1.235 + 0.001pb)$
Wiggins (1993)	$$\frac{q_o}{q_{0,max}} = 1 - 0.519167\left[\frac{p_{wf}}{p_r}\right] - 0.481092\left[\frac{p_{wf}}{p_r}\right]^2$$
Sukarno and Wisnogroho (1995)	$$\frac{q_o}{q_{o,max}} = FE\left[1 - 0.1489\left(\frac{p_{wf}}{p_r}\right) - 0.4416\left(\frac{p_{wf}}{p_r}\right)^2 - 0.4093\left(\frac{p_{wf}}{p_r}\right)^3\right]$$ Where:$FE = a_o + a_1\left(\frac{p_{wf}}{p_r}\right) + a_2\left(\frac{p_{wf}}{p_r}\right)^2 + a_3\left(\frac{p_{wf}}{p_r}\right)^3$ $$a_i = b_{oi} + b_{1i}.s + b_{2i}.s^2 + b_{3i}.s^3$$ Where: ao, a1, a2, a3, boi, b1i, b2i, and b3i are the fitting coefficients that are shown in Table 2.
Ilk et al. (2007)	$$\frac{q_o}{q_{0,max}} = 1 - v\left[\frac{p_{wf}}{p_r}\right] - (1 - v)\left[\frac{p_{wf}}{p_r}\right]^2$$
Al-Khadafy. A M et al. (2019)	$$\frac{q_o}{q_{0,max}} = 1.2359322 - 1.25646325\left[\frac{p_{wf}}{p_r}\right] + 0.0232948\left[\frac{p_{wf}}{p_r}\right]^2$$
H. Asaadian and M.K. Beyranvand (2020)	$$\frac{q_o}{q_{0,max}} = 1 - 0.3818\left[\frac{p_{wf}}{p_r}\right] - 0.6604\left[\frac{p_{wf}}{p_r}\right]^2$$

Table 2 Sukaro and Wisnogrho Correlation Constants

	b_{oi}	b_{1i}	b_{2i}	b_{3i}
a_o	1.0394	0.12657	0.0135	-0.00062
a_1	0.01668	-0.00385	0.00217	-0.0001
a_2	-0.0858	0.00201	-.00456	0.0002
a_3	0.00952	-0.00391	0.0019	-0.00001

Neural networks performed estimation modeling tools that have been used wide in many papers for modeling complicated real problems in Petroleum Engineering [4, 7, 8, 12, 17, 19, 23, 26, 27, 29] and also ANN is used to predict IPR [24,1 ,3]. Neural networks artificial can be defined as structures consisting of violently interconnected, adaptive simple processing elements able of implementing vast parallel calculations for knowledge performance and data processing [20, 22].

An artificial neural networks structure consists of neurons of artificial that are grouped into layers. The most common ANN structure consists of a number of interconnected neurons or nodes is shown in Fig. 1. Fig. 1 shows ANN model with two hidden layers. The first input layer takes data from external sources, and passes it to the network for processing. Then, the two hidden Layers will process them in a hidden way. The last output layer collects processed data and sends it out of the system. For ANN model, about 70% of the data is used to train the neural network as training sets and 30 % of data is used to test and validate the trained network [10, 25, 28].

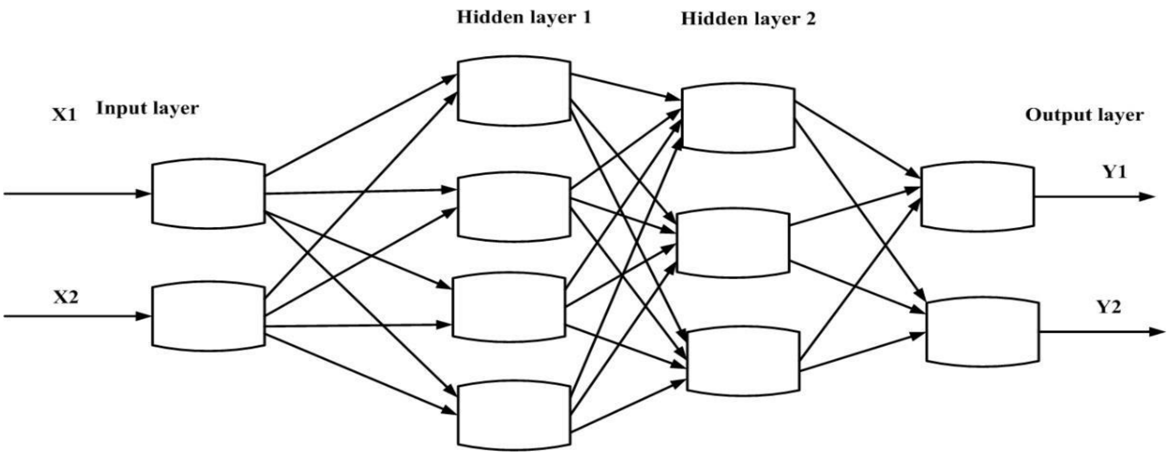

Figure 1 ANN model

Recently, artificial intelligence (AI) techniques such as artificial neural network (ANN), fuzzy logic (FL), and functional networks (FN) are being widely used for most of the petroleum engineering applications such as estimation of permeability[6], prediction two-phase inflow performance [18], prediction of pressure drop in two-phase vertical flow systems [2] , calculation of oil and gas properties [11], estimation IPR for vertical oil well in solution gas derive reservoirs [26], and calculation of inflow performance relationship of a gas field using Artificial Intelligence [1]. Artificial Intelligence provides functions which make modeling complex nonlinear systems easy as compared to a closed-form equation modeling. It possesses the learning ability from the given input data and further adapt to the input's environment. Also, it considers any weak assumptions regarding the physical phenomena which in turn affects for the generation of the input data.

2. Data Description

There are two production basins in Yemen they are Sab'atayn and Masilah basin which contain 55 Producing Fields and 2 national Oil Companies they are Safer and Petromasilah. TABLES 3 & 4 shows general information about producing blocks and reservoir and fluid properties in Sabatayn Basin in Yemen.

Table 3 General Information about Production Blocks in Yemen

Block Name	Governorate	Operator	Area (Km^2)	Start Year	Acum. Oil Production (MM BLL)	Avg. Daily Production (BOPD)	Number OF Fields
MARIB (18)	MARIB	Safer E&P Operation Co.	8,479	1986	1037.15	50.370	14
MASILA (14)	HADHRAMOUT	petromasilah	1,257	1993	1033.5	86.032	26
East SHABWAH (10)	HADHRAMOUT	petromasilah	964	1997	123.6	46.187	3
JANNAH (5)	SHABWAH	Jannah HUNT	280	1996	196.8	40.399	5
East SAAR (53)	HADHRAMOUT	DOVE Energy	474	2001	40.8	7.991	2
HWARIM (32)	HADHRAMOUT	DNO	592	2000	36.6	6.523	2
DAMIS (S1)	SHABWAH	OCCIDENTAL	1,156	2004	18.4	10.176	1
East AL-HAJR (51)	HADHRAMOUT	Canadian Nexen Yemen Ltd.	2,004	2004	30	12.050	3
South HWARIM (43)	HADHRAMOUT	DNO	1,622	2005	9.6	4.272	1
MALIK (9)	HADHRAMOUT	Calvally	2227	2006	6	4.347	3
W. AYAD (4)	SHABWAH	KNOC	1,998	1987	9.5	104	2
Al-Uqlah (S2)	SHABWAH	OMV	904	2006	7.1	14.484	1

Table 4 Reservoir and fluid Properties in SABATA Basin

Reservoir	Thickness (M)	Porosity %	Permeability Darcy	Block	Environment
Alif sand	≈ 280	18-25%	3	S1&18	Fluvial-deltaic
Intra salt dolomite	≈ 30	15-18%	2	S!&18	
Naifa	≈ 1000	18-25%	0.5	4&41	Sallow marine
Shuqra	≈ 400	15-18%	0.5	4	Sallow marine
Lam	≈ 600	12-25%	0.8	S1&S2	Deep marine
Kuhlan	≈ 10	15-18%	1	S2	Continental

The evaluation is performed by using data set obtained from analysis of wide range of Yemeni oil fields that collected from west, north, east and south of Yemeni oil fields (more than 20 fields and more than 200 wells) to get the best evaluation between correlations and to build model can prediction the IPR at any change of parameters and at any oil well in Yemen. For this study, more than 3000 data points which were collected from different Yemeni oil reservoirs are used. These data points include wide range variety of the following parameters (Pr, P_{wf} test, q_o test, q_o max, P_{wf}, J and P_b). The data ranges and description are presented in TABLE 5.

Table 5 Ranges of actual data

Parameter	Unit	Maximum	Minimum	Average
P_r	psia	4100	370	1660
P_{wf} (Test)	psia	3250	100	810
q_o (Test)	STB/D	3440	120	595
q_o (Max.)	STB/D	29200	220	1720
P_{wf}	psia	4100	15	850
J	STB/D/psia	11	0.5	1.3
P_b	psia	3480	50	535

Several authors have studied the multiphase flow phenomenon and have developed choke correlations using wellhead choke size and fluid properties such as wellhead pressure, gas-to-liquid ratio, specific oil gravities, specific gas gravities, and basic sediment & water. The essence of these choke correlations is to determine the oil production rate at specific fluid properties and choke size set points. This helps in oil production optimization and oil well performance analyses. However, most choke correlations created are not robust and are field-specific, and perform poorly for fields with process conditions different from those for which they were developed. Most developed choke correlations are only valid when fluid flows at critical flow. The choke
correlation by Gilbert [14] is the most extensively utilized choke correlation for critical flow. This correlation was developed by Gilbert using over 260 well-test data points from an oil field in California, USA. The wellhead pressure (sometimes called the upstream pressure), the gas-to liquid ratio (or gas-to-oil ratio), and the wellhead choke size (or choke diameter) are the only variables that affect this correlation [13, 30].

3. Research and discussion

This part will consist of two parts, first part will describe the evaluation between different methods (Vogel, Fetkovich, Klins and Majher, Wiggins, Sukarno and Wisnogroho, and Al-Khadafy. A M et al. models) to determine the inflow performance relationship for Yemeni oil fields and calculation average absolute percent error and R2 by using Excel program. Second part using Artificial neural networks software program to build a new model for prediction inflow performance relationship by using real Yemeni oil fields data.

Evaluation of different models was performed by comparing the results obtained by models and actual values. Calculations is conducted using real data gathered from different location of Yemeni oil fields. Summary of statistical analysis for selected correlations is given in TABLE 6 and Figs. 2 and 3. From TABLE 6 and Figs. 2 and 3, Khadafy. A M et al. model has the lowest average absolute error percent which is 8.6 %. The other methods have average absolute errors percent ranging of 12.3 %, 13.2 %, 18.6 %, 24.7% and 49.2 % for Wiggins, Fetkovich, Vogel, Sukarno and Wisnogroho and Klins and Majher, respectively. Also get the same results by using R^2, Khadafy. A M et al. model has 0.996 while the other methods have 0.992, 0.988, 0.982, 0.980 and 0.896 for Wiggins, Fetkovich, Vogel, Sukarno and Wisnogroho and Klins and Majher, respectively.

Table 6 Results of Statistical analysis

Models	Vogel	Fetkovich	Klins and Majher	Wiggins	Sukarno and Wisnogroho	Khadafy. A M et al
Average Error %	18.6	13.2	49.2	12.3	24.7	8.6
R^2	0.982	0.988	0.896	0.992	0.980	0.996
Standard deviation	14.22	11.24	65.25	9.38	18.96	3.55

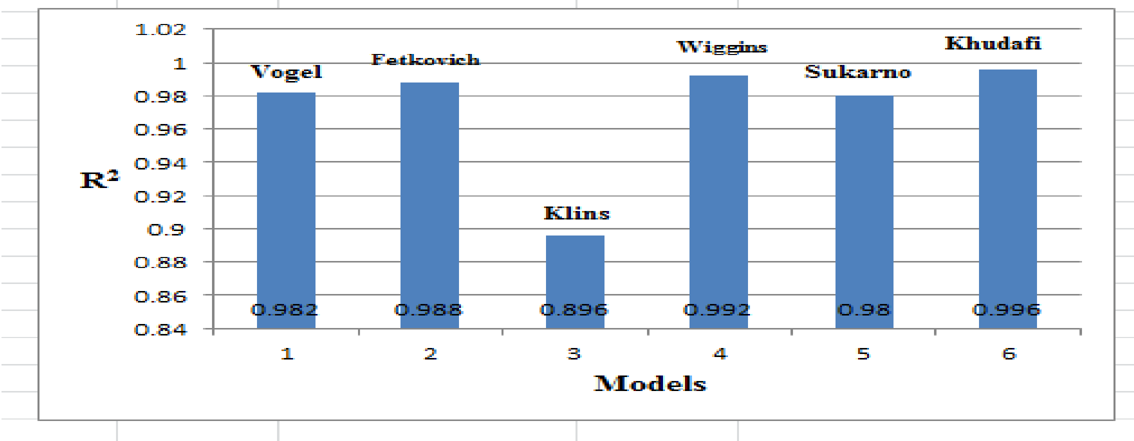

Figure 2. The average absolute error analysis

Figure 3 The R^2 analysis

Graphical tools aid in visualizing the performance and accuracy of a correlation. Figures 4 through 9 present cross plots of predicted flow rate by using correlations versus the actual flow rate. Investigation of these figures clearly shows that the Khadafy. A M et al. model outperforms all correlations.

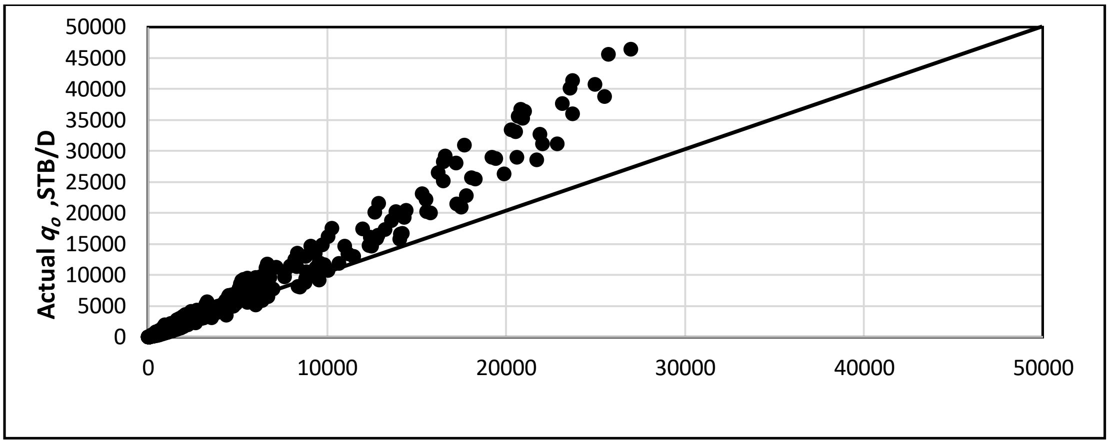

Figure 4 Cross plot of Observed vs. Calculated IPR Vogel correlation

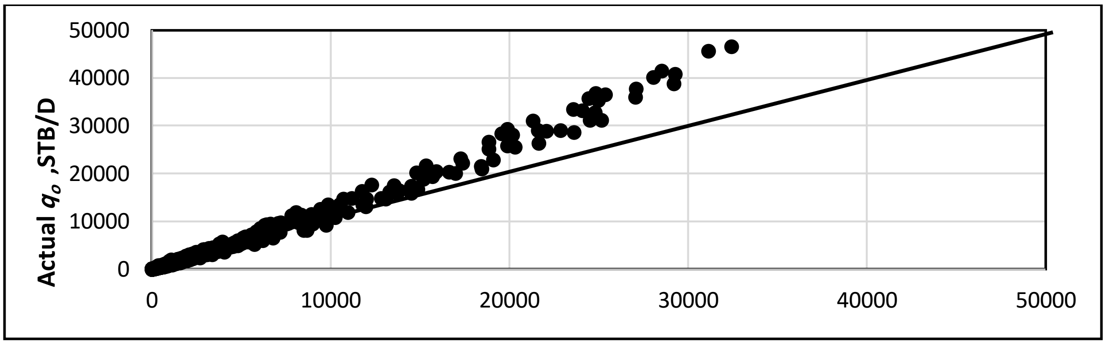

Figure 5 Cross plot of Observed vs. Calculated IPR Wiggin correlation

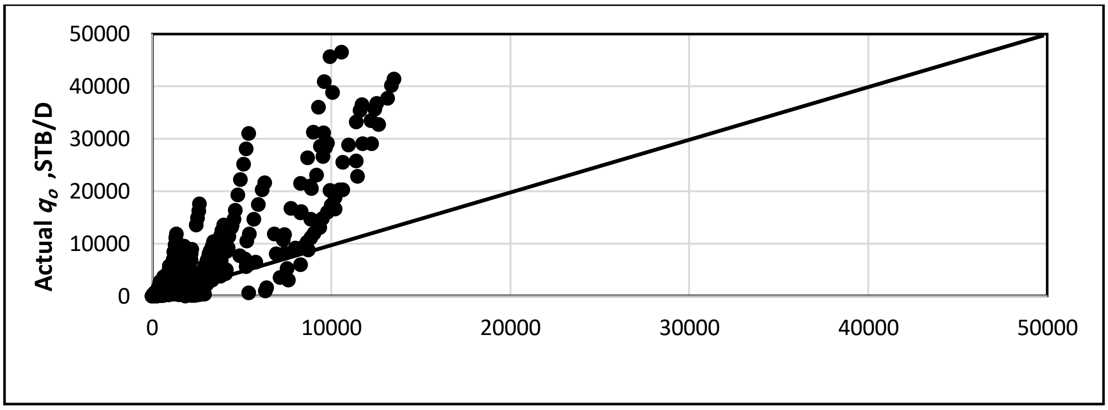

Figure 6 Cross plot of Observed vs. Calculated IPR Klins-Clark correlation

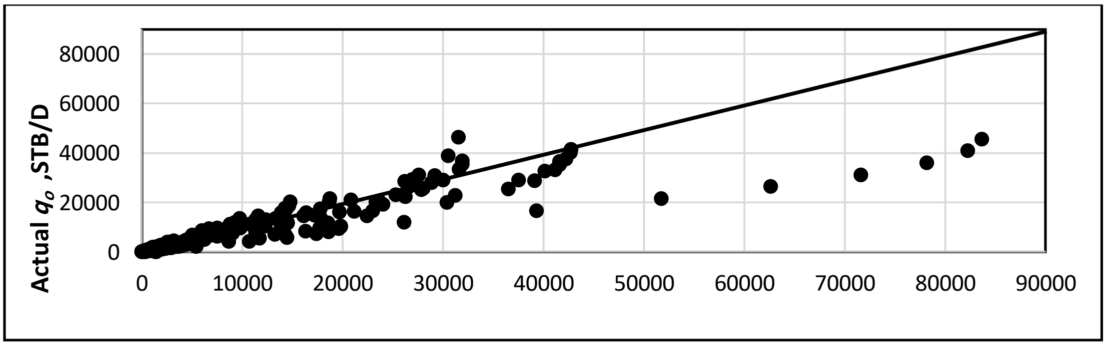

Figure 7 Cross plot of Observed vs. Calculated IPR Fetkovich correlation

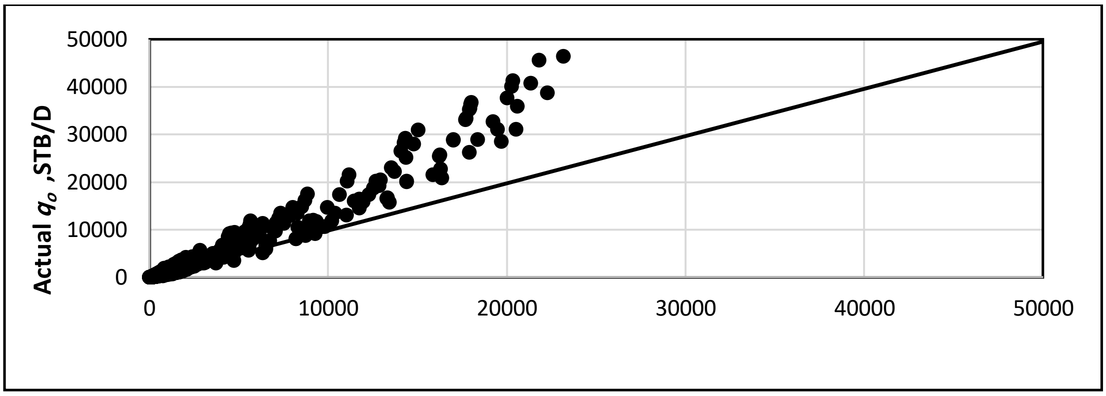

Figure 8 Cross plot of Observed vs. Calculated IPR Sukarno correlation

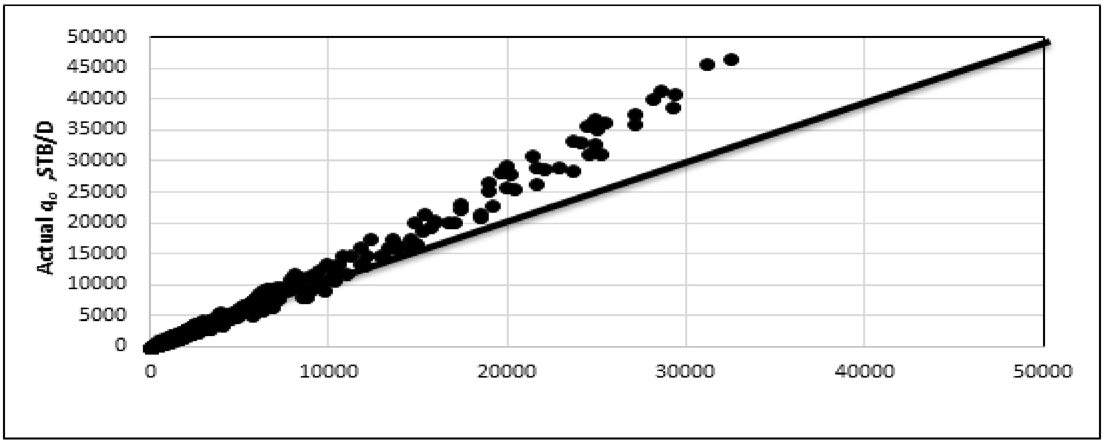

Figure 9 Cross plot of Observed vs. Calculated IPR Khadafy. A M et al. correlation

To training set about 70 % of data is used, 15% of data is used to validation set and to test he model 15 % of data is used (Table 7). Architecture of Neural network (number of neuron and input layer, layer of hidden and number of neurons in layer of hidden) was choose manually. Layers of hidden activation, function of error and function of activation are also defined. Data preprocessed using scaling range: (-1.1) for input parameters. Output variable was transformed to a scale between 0 and 1. The network training is accomplished by Levenberg-Marquardt algorithm. The network is trained by iterations process. When desired error is achieved training stopped and the best network was tracked when best correct calculation rate is get.

Overtraining is identified using the Validation set. The situation when the network error increases on the validation set during several iterations while still decreasing on the Training set is identified as the starting point of overtraining. Neural network automatically tested after training completion. In the testing process, the actual flow rate vs. output flow rate are compared error values for each data point from the input dataset is calculated.

Table 7 Statistical Description of the input data used for training and validation

Parameter		p_r, psia	$p_{wf\ test}$, psia	$q_{o\ test}$, STB/D	$q_{o,\ max}$, STB/D	p_{wf}, psia	J, STB/D/psi	p_b, psia
Maximum		4164.5	3263	3444	29196.6	4164.5	10.4	3450
Minimum		366	71	116	210.8	0	0.05	34
Average		1655.4	749.8	583.7	1708.2	821	1.1	520.5

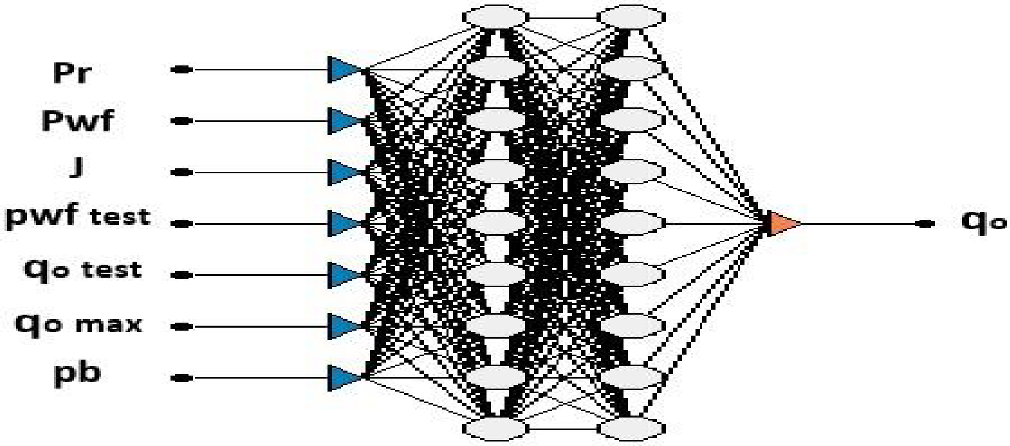

Figure 10 Developed ANN model

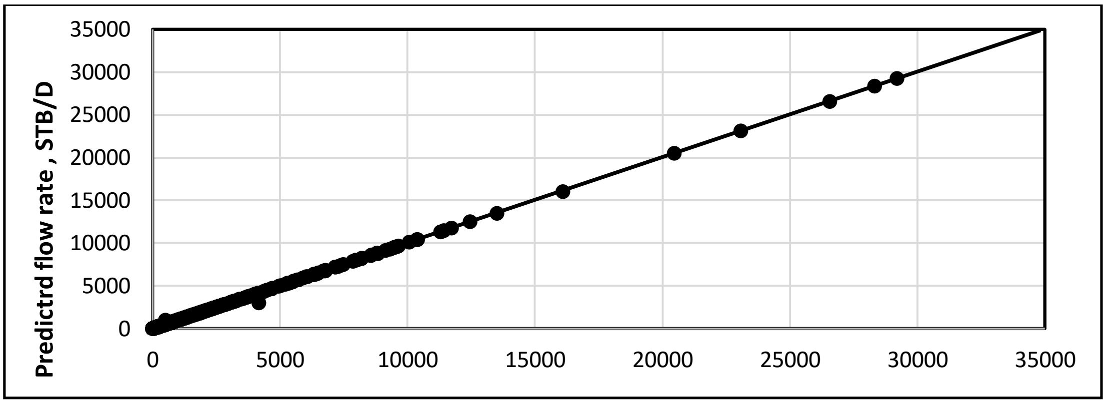

Figure 11 Cross plot between actual data versus prediction data from new model

The performance and validity of ANNs models was estimated by coefficient of correlation R^2 and Absolute average error AAPE. TABLE 8 statistical comparison between the best correlation with new ANN model, it is shown that developed model provides with best results contrasted with empirical correlations. Fig. 11 shows the cross plot between actual flow rate with the flow rate that predicted by the developed model, it is showed that the accuracy of the developed model is very good.

Table 8 Comparison between best correlation and ANN Model

Model	Average Error %	R^2	Standard deviation
Khadafy. A M et al	8.6	0.996	3.55
ANN model	0.98	0.9997	0.85

4. Conclusions

From the results obtained from this paper, the following conclusions can be pulled: -

- The error analysis is utilized as a comparative criterion for the testing of the evaluated correlations for prediction IPR against actual data using Yemeni data.
- Evaluation between correlations shows that the Khadafy. A M et al correlation is the best with lowest absolute average error 8.6 %, the lowest standard error deviation 3.55 and the largest R^2 0.996 compare to the other correlations used in this study.
- A new Artificial Neural Networks model was developed to predict IPR. Validation of the method was done by comparison the model with the best empirical correlations which indicate that the proposed model outperforms others empirical correlations.
- A new Artificial Neural Networks model was examined by real Yemeni data and gives the best results are obtained from new model and based on the results obtained it's recommended to use the developed model to predict IPR.
- The new Artificial Neural Networks model can be used for all Yemeni fields to predict IPR and this well reduce the cost that it is result from using several correlations for predict IPR.

NOMENCLATURES

AAPE = Average Absolute Percent Relative Error

IPR = Inflow Performance Relationship
ANN = Artificial Neural Networks
R^2 = Correlation Coefficient Squared
J = Productivity Index of the reservoir (PI), STB/D/psia
a_o, a_1, a_2, a_3 = Constants for Sukarno and Wisnogroho, dimensionless
b_{oi}, b_{1i}, b_{2i}, b_{3i} = Constants for Sukarno and Wisnogroho, dimensionless
n = Fetkovich deliverability exponent, dimensionless
P_b = Bubble Point Pressure, psia
P_r = Average reservoir pressure, psia
P_{wf} = Bottom hole flowing pressure, psia
q_o = Oil flow rate, STB/D
q_{omx} = Maximum oil flow rate, STB/D
$P_{wf\ test}$ = Bottom hole flowing pressure from tested point, psia
$q_{o\ test}$ = Oil flow rate from tested point, STB/d

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CONTRIBUTION

Khaled Ba-Jaalah prepare the paper and NN approach, Ghareb Hamada revise the paper and discussion of results, Salim Baarimah prepare the paper and collect data and Faleh AlMehdawy revise the paper and discussion of results.

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