Proposing a New Model for Estimation of Oil Rate Passing Through Wellhead Chokes in an Iranian Heavy Oil Field

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***Abstract*— One of the main duties of production engineers is to maintain the reservoir productivity and keep it at a desirable level during the production time by preventing extra production and controlling the production through wellhead chokes. Wellhead chokes are tools that are installed in flowing pipes to resist the pressure, limit and control the production, prevent water and gas coning, and control the pressure in order to maintain the wellhead equipment in good working order. Wellhead chokes, which are installed in well flow, are divided into two main groups: positive or fixed chokes and adjustable or variable chokes. Passing flow rate through wellhead chokes is a function of wellhead pressure, choke diameter, before choke temperature, and water production rate. The objective of this work is to propose a new model for the estimation of the oil rate passing through wellhead chokes. In this study, 180 actual tested data for 5 wells from a heavy crude oil field were used to develop a new model for estimating oil rate passing through wellhead chokes. The proposed model has an average relative error of about 5.8%.**

Keywords— Heavy crude oil reservoir, wellhead choke pressure, choke size.

I. Introduction

Heavy oil reservoirs are types of reservoirs in which the temperature is lower than the critical point temperature [1, 2]. This type of reservoir is divided into three types: 1) heavy crude oil reservoir, 2) ordinary oil reservoir and 3) volatile crude oil reservoir [3]. The reservoir under investigation is heavy crude oil, the properties of which are shown in Table 1 and the phase diagram in Figure 1.

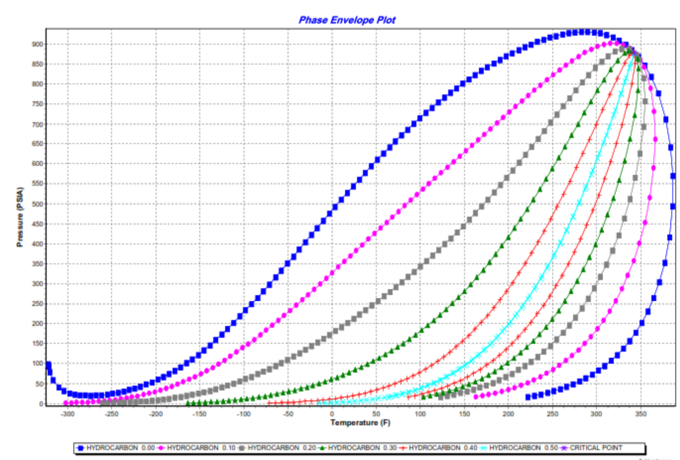

Fig. 1. Phase diagram of heavy crude oil reservoir.

A petroleum engineer's primary responsibility is to increase production lifetime by preventing extra production, controlling production through chokes, and increasing production or reservoir lifetime by selecting an appropriate choke on production wells. A wellhead choke is a tool that is installed through an inflow pipe path to resist pressure, limit and control production, prevent water and gas coning, and control pressure in order to keep the wellhead equipment in good working order [2, 3].

TABLE I. FLUID PROPERTIES OF OIL FIELD.

Fluid properties	Symbol	Rate	Explanation
Initial pressure, Psi	P_i	5026	Undersaturated Oil Reservoir at (5026 psia, 198 ^{0}F)
Oil formation volume factor, bbl/STB	B_o	1.474	
Oil viscosity, -	μ_o	4.4	
Bubble point pressure, Psi	P_b	2785	
^{0}API Gravity of Residual Oil, -	API	11-14.1	
Average Compressibility Factor, 1/Psi	C_o	$13.24*10^6$	
Solution Gas Oil Ratio=Rsi, Scf/STB	GOR	767	
Reservoir Temperature, ^{0}F	T	198	

The flow rate through the choke is determined by the wellhead pressure, choke diameter, before choke temperature, and water production rate, which includes free water, sediment water, emulsion, and gas oil ratio (Equation 1).

$$Q_L = f(P_{wh}, D_{64}, T_u, BS\&W\%, GLR) \quad (1)$$

The passing flow rate is primarily two-phase, and it can produce two types of flow when it passes through flow chokes: critical or sonic flow and sub-critical or sub-sonic flow. Figure 2 shows that if the pressure rate after the choke (P2) to before the choke (P1) is less than 0.588, the flow is critical; otherwise, it is sub-critical [4]. According to studies, the flow in Iran oil wells of southern crude oil fields is critical, while some condensate gas wells are subcritical.

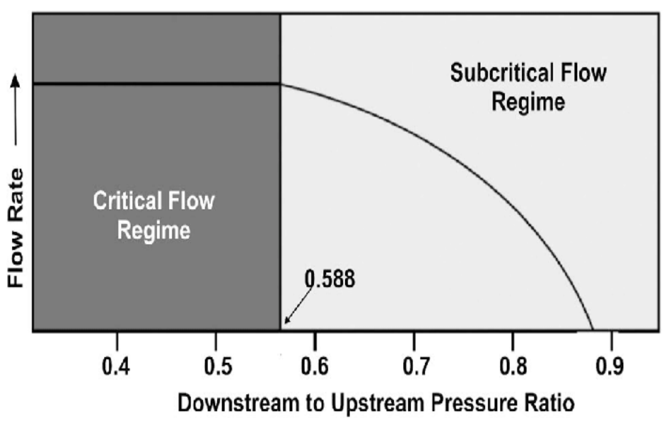

Fig. 2. Diagram determining critical and subcritical flow in wellhead choke.

Wellhead chokes which are installed through wells flow, are divided into two main groups that are:

- Positive or fixed choke
- Adjustable or variable choke

A. *Positive or fixed choke*

Positive or fixed chokes are used when the production rate is constant for a long time and the production sand or fluid is corrosive (Figure 3).This choke has the following properties:

- Constant bore diameter
- Choke is Ceramic, Tangestan carbide or iron type
- Choke length can be from 2 to 6 inches

Fig. 3. An illustration of fixed choke

B. *Adjustable or variable chokes*

An adjustable or variable choke is installed to adjust the flow rate on the wall, and by rotating it, it varies the entry pulley. In wells which have sand production problem, gate valve is not used to decrease or increase the flow, because in addition to sever erosion and corrosion, sand causes blocking of some part of well column and as a result, it results in a wellhead flow pressure drop and also wellhead equipment erosion. This kind of choke is classified into two groups: Type 1, is similar to a needle valve and has a handle, by which turning the flow can be decreased or increased. The valve handle has gradation and it shows the equipment diameter (Figure 4). Type 2 has two disks, each with two pores, one of which is constant while the other two rotate to adjust the appropriate flow rate (Figure 5) adapted from [5].

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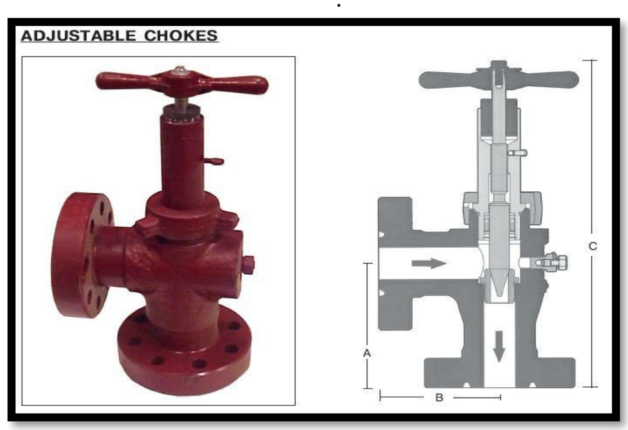

Fig. 4. An illustration of the type 1 chokes.

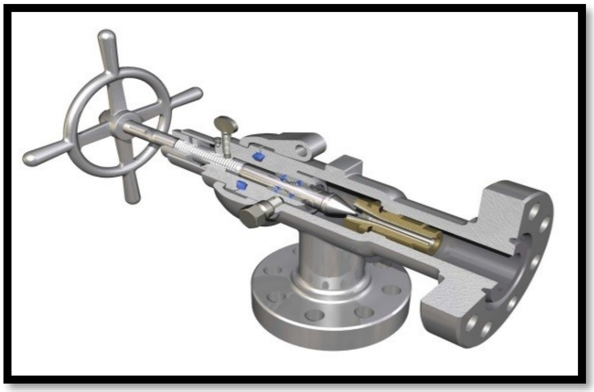

Fig. 5. An illustration of the type 2 chokes.

II. Literature Review

For the first time, in 1949, Tangern et al. proposed a multiphase fluid flow theory in chokes. This theory is applicable when liquid is a continual phase (volumetric gas rate to liquid is less than one) [6]. In 1954, Gilbert provided an empirical relationship using 268 test data for choke size between 6/64 and 18/64 [7]. The second empirical relation was proposed by Baxcendell in 1957, based on the Gilbert equation with more data [8]. In 1960, Ros proposed his work based on Tangren's theory for the state in which the gas is the continuous phase. The third empirical relationship was proposed by Achong in 1961. He claimed that when we compare 104 tests of fluid flow from flow within chokes that their diameter is between 1-1.2 to 4 inches, better results are obtained [9]. After Achong, in 1963, Poettmann and Beck changed the Ros model into a field unit and they introduced a model which is used only for critical flow and it depends on pipe pressure or downstream pressure [10]. In 1969, Omana determined his analyses based on eight groups of important dimensionless equations and carried out some experiments using natural gas and water systems, and he obtained a relationship which was in the range of choke sizes of 4/64 inches and a production rate maximum of 800 gallons per day [11]. In 1972, Fotunati also suggested two relations for sub-critical and critical flow, for which Medivedive and Guzov logs were used [12]. In 1975, Ashford and Pierce proposed a relationship for sub-critical flow under certain conditions. These conditions are: 1) liquid is incompressible, 2) flow is not isotropic and between slippage phases. None of the above researchers have investigated the production water, but in this study, it was investigated the Gilbert equation (without considering the production water and temperature) for heavy crude oil fields and compared the calculated error rate with which its results are expressed in Table 5.

A. *Empirical relations for crude oil wells*

As we know, most of the proposed relations are related to crude oil wells and empirical relations are better than theoretical relations in terms of time and expenses. The overall form of proposed relation by Gilbert, Ros, Baxcendell and Achomg is as follows (Equation 2) (Alrumah, 2007):

$$Q_L = \frac{P_{wh} \times {D_{64}}^{A_3}}{A_1 \ \times GLR^{A_2}} \tag{2}$$

Where, QL represents the liquid production rate (bbl/day), GLR is gas-liquid ratio (SCF/STB), and P_{wh} stands for well (or tubing) head pressure (psi), in addition, D_{64} is bean size (1/64) inch, and A_1, A_2, A_3 are the empirical constant.

TABLE II. SHOWS CHOKE COEFFICIENTS FOR MOST COMMON EMPIRICAL RELATIONS OF OIL RESERVOIRS.

Researchers	Published year	Correlation	Empirical Coefficient		
			A_1	A_2	A_3
Gilbert	1954	2	10.0	0.546	1.890
Baxcendel	1957	2	9.56	0.546	1.930
Ros	1960	2	17.4	2.00	0.500
Achong	1961	2	3.82	0.650	1.880

B. *Empirical relations for gas condensate oil wells*

The first empirical relation for gas and gas condensate two-phase flow was provided by Osman and Dakla in 1990. To obtain this relation, data related to eight wells of a gas condensate reservoir around the Persian Gulf were used, and after that, Nasriani et al. (2011) carried out their research on a gas condensate reservoir in Iran, and after him, Leal et al. (2013) studied a field located in Saudi Aramco [13]. The overall form of the relation is so similar to Gibert's relation with some modification, which is shown as (Equation 3):

$$Q_g = \frac{P_u \times {D_{64}}^{b_1}}{b_2 \ \times CGR^{b_3}} \tag{3}$$

Where: Q_g= gas production rate (MMScf/day), CGR= condensate gas ratio (SCF/STB), P_u= upstream pressure (psi), D_{64}=bean size (1/64) inch, and b_1, b_2, b_3= empirical constant. Table 3 shows choke coefficients for some researchers from gas condensate wells.

TABLE III. CHOKE COEFFICIENTS FOR SOME RESEARCHERS FROM GAS CONDENSATE WELLS.

Researchers	Published year	Correlation	Empirical Coefficient		
			b_1	b_2	b_3
Osman & Dakla [14]	1990	3	1.85	4.127	0.434
Nasriani & Kalantariasl [13]	2011	3	1.83	1.624	0.736
Jario et al. [15]	2013	3	1.7533	81756.5	0.0652

III. Data Analysis

In this study, we used 180 production test data from 5 wells, which are located in one of the heavy crude oil fields in Iran.

The gathered data is between the years 2006 to 2013, and we can see the production history by changing choke diameter and production rate in Figure 6.

The pattern of locating the wells in the field has been simulated by a software (Pipesim) which is shown in Figure 7. The pattern of this field and its wells has also been simulated by a software (Pipesim) which is shown in Figure 8, and the pressure drop of wells along with choke and flow pipes has been shown in Figure 9. The used data range is also shown in Table 4. By considering all the available data and also simulations, a new Model for Estimation of Oil Rate Passing Through Wellhead Chokes has been proposed that is shown in Equation 10.

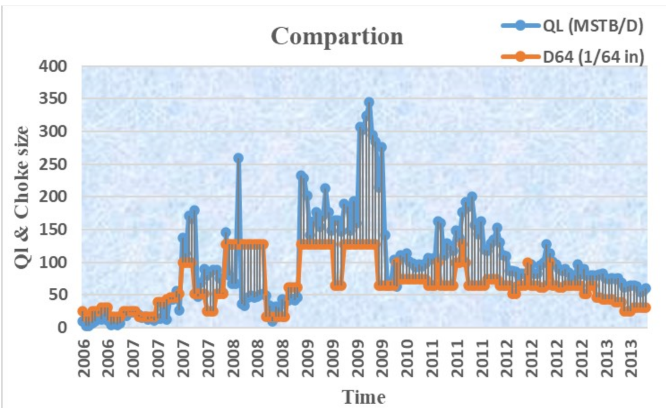

Fig. 6. An illustration of production history by changing choke diameter and production rate.

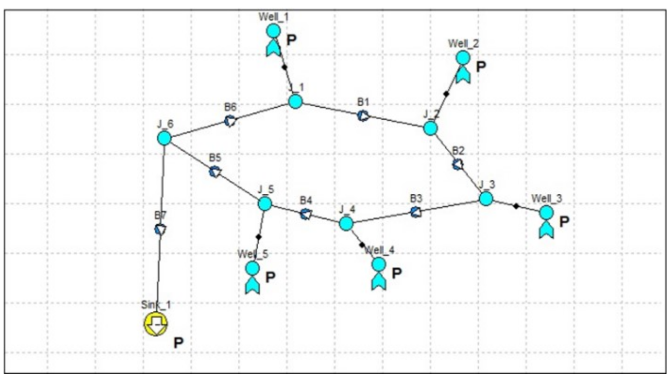

Fig. 7. A pattern of the way of selecting wells in this field.

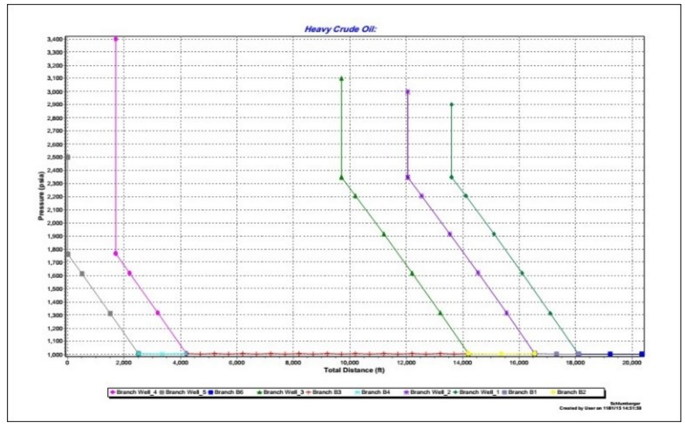

Fig. 8. Pressure drop of the wells in this field.

TABLE IV. THE RANGE OF USED DATA FOR OIL FIELD.

Choke diameter	**Gas liquid ratio**	**Temperature**	**Water production percent**	**Liquid production**	**Wellhead pressure**
D64, inch	GOR, Scf/STB	T, 0F	BS&W %, -	QL, STB/D	Pwh, Psi
23-64	40-900	80-190	0.02-66	205-34450	100-1150

IV. METHODOLOGY

By simplifying equation 1, we obtained a three unknown variable equation and in order to solve that, three equations are created, and through the Gauss-Jordan method, we solve it as a matrix. To simplify the work by C# software, code is written and by creating a screen with certain entries, output is revised and we do the same for equation 3 as equation 1, but in equation 3 we make five equations, five fabulous, and then solve that. For these equations and for production rate, four error types are defined as follows.

$$E_r = \frac{Y_{exp} - Y_{est}}{Y_{exp}} \times 100 \tag{4}$$

$$E_{ar} = \frac{\sum_{i=1}^{N} \frac{Y_{exp} - Y_{est}}{Y_{exp}}}{N} \tag{5}$$

$$E_{aar} = \frac{\sum_{i=1}^{N} \left| \frac{Y_{exp} - Y_{est}}{Y_{exp}} \right|}{N} \tag{6}$$

$$E_{min} = min \frac{Y_{exp} - Y_{est}}{Y_{exp}} \tag{7}$$

$$E_{max} = max \frac{Y_{exp} - Y_{est}}{Y_{exp}} \tag{8}$$

$$SD = \left\{ \frac{\left(\sum_{i=1}^{N} \left| \frac{Y_{exp} - Y_{est}}{Y_{exp}} \right| - E_{aar} \right)^2}{N-1} \right\}^{0.5} \tag{9}$$

By considering the Gilbert equation, a New Model is formed as equation 12:

$$Q_L = \frac{P_{wh} \times D_{64}{}^{A_3} \times (1 - BS\&W\%)^{A_4} \times \left(\frac{T_u}{T_{Sc}}\right)^{A_5}}{A_1 \times GLR^{A_2}} \tag{10}$$

Where; $A_1 = 15.71$; $A_2 = 1.42$; $A_3 = 0.54$; $A_4 = 1$; $A_5 = -0.213$

V. Result and Discussion

The following results have been proposed based on 180 data related to five wells of one of the heavy crude oil fields in the south-west of Iran, which are classified into two groups of tables and figures:Figures 9 and 10 show the comparison of the real production rate and the estimated rate for this study and other researchers. These figures show the accuracy of this study is higher than that of another researcher.

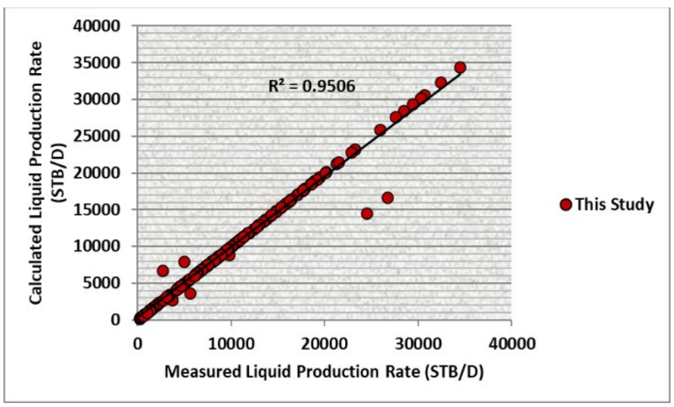

Fig. 9. Comparison of measured and calculate production rate for this study.

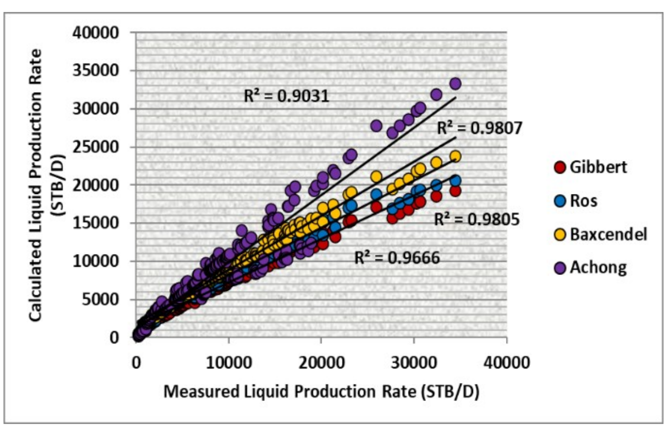

Fig. 10. Comparison of measured and calculate production rate for other researchers.

Figure 11 shows temperature and water production as a function of production rate. Based on this figure, two parameters, T and BS&W, are effective on the Q_L. So, by inputting these parameters into the equation, one can increase the accuracy of the prediction of flow rate.

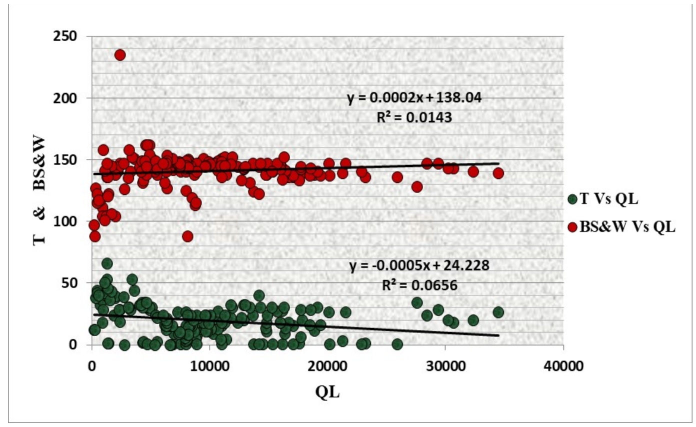

Fig. 11. Comparison of measured and calculate production rate for this study.

Figures 12 and 13 show the error rates for this study and other researchers, and Table 5 shows the present error rate for this study and other researchers' works. Figures 12 and 13 and Table 5 show this work is better than another researcher's equation.

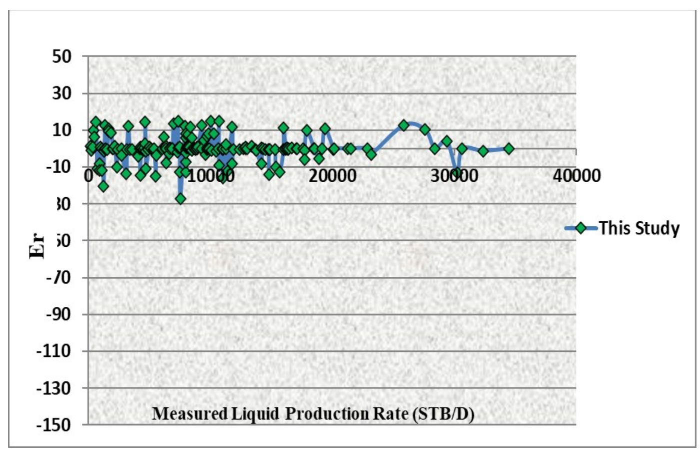

Fig. 12. Determination of error between measured and calculate production rate of equation 4 for this study.

VI. Discussion

The proposed method provided promising results. The comparison of measured and calculate production rate and also the comparison of measured and calculated production rate of former researchers shows an acceptable accuracy. In addition considering the determination of error between measured and calculated production rate of equation 4 and also the determination of error measured and calculated for production rate of equation 4 for former studies are in acceptable range. However, the method can be improved using further AI-based algorithms, e.g., [15-24]. In fact, using ensemble, hybrid, or deep learning methods, e.g., [25-36], can significantly improve the model quality. For the future study, we aim at employing novel methods, e.g., [37-42] for improving the accuracy and precision of the model.

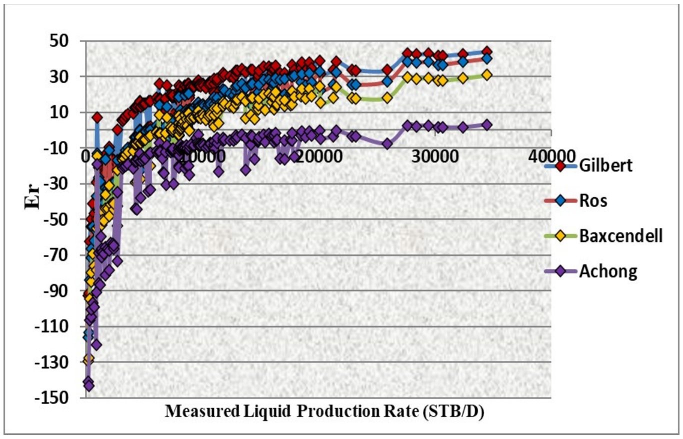

Fig. 13. Determination of error measured and calculate production rate of equation 4 for other researchers.

TABLE V. SHOW PRESENT ERROR RATE FOR THIS STUDY AND OTHER RESEARCHERS WORKS.

Researchers	Average relative error	Average absolute relative error	Min average absolute relative error	Max average absolute relative error	Standard deviation
Gilbert	28.87	25.1	0.32	92.68	17.09
Ros	19.42	19.83	0.15	116.16	12.83
Baxcendell	-16.93	18.47	0.14	129.47	10.47
Achong	-9.86	14.28	0.10	83.11	8.28
This study	3.8	5.82	0.057	14.33	6.79

VII. CONCLUSON

In this study, we have used the C# program, which is one of the most powerful math estimator software. It gives us an absolute relative rate of between 0.057 and 14.23, which is very close to the real rate. The results show that the obtained equation used in this study is more accurate than other researchers' results. This study aims to obtain a relation which can estimate the production rate for heavy crude oil reservoirs along with water production with less error. One of the main goals of petroleum engineering is to increase production lifetime by preventing extra production, controlling production through choke, and increasing production time or lifetime through selecting an appropriate choke diameter, which can be estimated by this model. The illustration of the production history shows choke changes, which, as you see, in 2009, increased choke diameter and have made the reservoir time increase and decrease by choosing an appropriate choke between 2010 and 2011, has resulted in production control and an increasing production lifetime.

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