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Efficient estimation of maximum flow rates through Chokes during Petroleum Production Operation

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Abstract
One of the challenging subjects in petroleum production engineering is to calculate flow rates through chokes and orifices accurately. Variety of empirical correlations and analytical models have been developed so far, and most of them have acceptable results just in their domain of measured data. Lack of a method which gives the decent match with measured data is a necessity regardless of the type of the fluids and input parameters ranges. This article presents advanced methods to estimate the gas flow rate through choke. The database includes around 1600 data with a wide range of input parameters. The methods are included feed-forward artificial neural network (ANN), least square support vector machine(LSSVM), decision tree (DT) analysis. Based on the results, decision tree with less than 1% error makes the perfect modelling of choke flow rate. ANN and LSSVM with 2% error have reliable results. Besides, a model has been developed based on gene expression programming(GEP) which shows correct results just in low gas flow rates.

Keywords: *Choke; DT; ANN; LSSVM; GEP; ANFIS; Gas Rate.*

1. Introduction

In the petroleum production engineering, chokes and orifices are instruments which are used to regulate the flow rate of producing wells and they are usually installed after well head. There are two general types of chokes: positive chokes and adjustable chokes [1]. The reasons for having a choking device in the production system are to [2]: 1) protect reservoir and surface equipment from pressure fluctuations; 2) avoid sand problems due to high drawdown; 3) control flow rate to avoid water or gas coning; 4) produce the reservoir at the most efficient rate.

There are two types of flow in surface chokes: critical and subcritical. During critical flow, fluid velocity in choke restriction is higher than sonic velocity, and in this situation, the flow rate is independent of downstream pressure. Mach number for the fluid is greater than or equal to one for critical flow [1]. In opposite, the flow rate in the subcritical state is a function of downstream and upstream pressure both.

In this work, a literature review has been done to analyses different empirical and analytical models. Afterwards, based on the available data, choke multiphase flow modelling will be done by three advanced regression methods including decision tree (DT) modelling, Feed-Forward neural network analysis (ANN) and least square support vector machine (LSSVM) approach. Additionally, a new model, which has been developed based on gene expression programming (GEP) and incorporates the main input variables to calculate choke flow rate is presented. For the first time, decision tree algorithm as one of the powerful models has been applied to estimate gas flow rate through well head chokes, and which shows highly accurate results in comparison to existing models including empirical correlations, analytical models and also ANN and LSSVM.

2. Literature review of the existing models and correlations

There are various equations and models which predict volume flow rate of chokes and orifices. In this section, the most well-known ones will be reviewed. Perkins developed an analytical model encounter isentropic (adiabatic with no friction loss) flow of multiphase hydrocarbons and water in chokes. It has been derived based on the general energy equation which is valid for critical and subcritical flow [3]. Based on this model, Rahimzadeh *et al.* developed a choke multiphase flow model for a gas condensate reservoir. The model was accuracy evaluated by incorporating a gas condensate field DST and production test data. Nomination of well potential after clean up and well stimulation, appropriate design of the production test and well production allocation in platforms; are some of the main applications of this work. In this paper, in addition to analytical modelling, a new empirical correlation which incorporates the water content has been derived which is showed in the following [2].

$$Q = 0.0253 \times \frac{P_{wh} \times Size^{1.845} \times \left(1-\frac{BSW}{100}\right)^{0.1374}}{0.0878} \qquad (1)$$

where Q = Gas Rate, MMSCF/D; Pwh = Well Head Pressure, psia; Size = Choke Size, in; BSW = Water Cut (W/W+O), %; CGR = Condensate Gas Ratio, STB/MMSCF

Sachdeva derived a choke model for prediction of critical and subcritical multiphase flow rates, which was evaluated using measurement field data. The accuracy of the model has been concluded based on real data [4]. Guo *et al.* used a comprehensive data base of oil and gas condensate wells to improve choke flow model performance, which was found that by optimizing the discharging coefficient, the accuracy of prediction is enhanced [5].

There are various empirical correlations which basically use the same parameters with the different coefficients which were tuned based on specific databases. Osman et al. derived an empirical correlation of choke flow for a gas condensate reservoir which is located in Middle East [6]. The correlation is presented as follows:

$$P_1 = 767.2 \times Q_g \times \frac{LGR^{0.5598}}{S^{1.8298}} \qquad (2)$$

where P_1 is well head pressure (psia), LGR is the liquid-gas ratio (STB/MSCF), Q_g is gas flow rate (MSCF/day), and S is choked size in 64th inches [6].

Most of the empirical correlations can be presented in the following form. They tried to assign a proper relationship between wellhead pressure and flow rate

$$P_{wh} = \frac{A_1 Q_L GLR^{A_2}}{d^{A_3}} \qquad (3)$$

where P_{wh} is well head pressure (psia), GLR is the gas-liquid ratio (SCF/STB), Q_L is oil flow rate (STB/day), and d is choked size (inch).

Gilbert was the first to present such a relationship based on field data collected from the Ten Section field of California. Ros also presented relationships that are often used. Baxendell and Achong also modified the correlation coefficients. Table 1 summarizes the parameters for each equation [7-10].

Table 1. Empirical correlations coefficients

Model	A_1	A_2	A_3
Gilbert	3.86×10^{-3}	0.546	1.89
Ros	4.26×10^{-3}	0.500	2.00
Baxendell	3.12×10^{-3}	0.546	1.93
Achong	1.54×10^{-3}	0.650	1.88

Ashford *et al.* developed mathematical models and empirical correlations to analyse dynamic behavior of multiphase flow through orifices, and most of them were tested with field data. Validity in both critical and subcritical flow regimes were evaluated as well. Pressure drops in choke were related to fluid properties and choke sizes. Some of them incorporate temperature as an input parameter. As mentioned earlier, optimization of discharge coefficient in these models is used to increase the accuracy of prediction [11-12]. Al-Attar *et al.* compared available equations of multiphase flow through chokes. This assessment was made based on statistical analysis of more than 100 well tests [13]

Fortunati determined accurate liquid flow rate based on the corrected velocity of the mixture in downstream of chokes. This model was applicable for critical and subcritical flow [14]. One of the missing parameters in most of the empirical correlation is water quantity. Safar Beiranvand *et al.* [15] presented a new form of the empirical equation which uses basic sediment and water (BS&W) as a new input parameter along with other conventional inputs such as well head pressure, gas oil ratio and chokes size. Having optimized, relevant coefficients of input parameters were shown based on Iranian oil field which includes production data from different wells [15].

Advanced models such as neural network and support vector machine have been reported to calculate choke flow rates in some articles. Al-Khalifa used Artificial Neural Network technique as a practical tool to estimate flow rates through chokes and selection of optimal orifice dimensions. This model gives precise answers in comparison to measured field data and works in wide range of input parameters [18]. ZareNezhad studied the performance of gas condensate flow through chokes by use of the neural network. The network was trained using Levenberg-Marquardt back-propagation method, and transfer function which was applied was a hyperbolic tangent sigmoid function [19]. Gorjaei *et al.* derived a least square support vector machine (LSSVM) algorithm to forecast liquid flow rate in two-phase flow in surface chokes. Particle swarm optimization (PSO) is applied to improve tuning constraints of LSSVM model. Model inputs include choke upstream pressure, the gas liquid ratio (GLR) and choke size which are surface measurable variables [20]. In a similar work, Nejatian *et al.* developed a model using Least-Squares Support Vector Machine (LSSVM) method to estimate choke flow coefficient in both nozzle and orifice type chokes in subsonic gas flow [21].

3. Development of New Models

To develop reliable models, a comprehensive dataset is required. The database collected covers different variables viz. choke size (24-72, 1/24 inch), well head pressure (896-3787, psia), BSW (0-15, %), gas rate (5-94, MMscf/d), oil rate (58-4307, bbl/d), and water rate (0-179, bbl/d). In the DST operation, the wells are producing at a series of different stabilized flow rates in different chock sizes, typically with a sequence of increasing flow rates. In the mean while measuring the stabilized bottom hole flowing pressure at the sand face, wellhead pressure, water content, oil and water rate are executed. In this study, 1597 test points were taken with acceptable ranges for different input parameters.

All the models including DT, ANN and LSSVM and also GEP based model were coded in MATLAB software to analyze the data and recognize the patterns. The statistical error parameter used in this study is average absolute relative deviation (AARD).

$$AARD\% = \frac{1}{n}\sum_{i=1}^{n} E_i\% \quad \text{where} \quad E_i\% = ABS\left[\frac{X_{\exp} - X_{\text{rep./pred}}}{X_{\exp}}\right]\times 100 \Rightarrow i = 1,2,3,...,n \tag{4}$$

To validate the accuracy of the models with data which were not used in training the models, about eighty percent of database was separated for training and the rest was assigned for testing the ANN, LSSVM and DT approaches.

A significant information that can be obtained from data mining tasks is the decision tree (DT). A decision tree is a method to recognize dominant patterns in data series as tree structures. The objective of using the decision tree is to obtain an accurate representation of the relationship between input and output parameters. One of the main advantages of DT is visualization of structure; unlike neural networks, it is not a "black box." The tree is composed of a root node, a set of internal nodes, and a set of terminal nodes (leaves). Each node of the decision tree structure makes a binary decision that splits either one class or some of the classes from the remaining classes [22-23]. The regression DT toolbox available in the MATLAB software was used to develop a model for comparing the predicted values with the other methods. Input parameters of the DT model are BSW which expresses the ratio of water rate in total liquid rate, choke size (1/64 in), well head pressure (psi) and CGR is condensate to gas ratio (STB/MMscf). The output parameter is Qg which stands for choke gas flow rate (MMscf/d). In the following, the results are presented. The AARD value of the model is 0.4 %. Same input variables were employed for the development of a reliable model on the basis of adaptive neuro-fuzzy inference system (ANFIS) algorithm. ANFIS was proposed by Jang in 1993 [24] which is accounted as a smart hybrid methodology composed and or combined with both fuzzy logic and artificial neural network. The AARD obtained for estimation of choke flow rate by using ANFIS is 43 %.

Neural Network is an information processing method based on the biological nervous systems, such as the brain, process information. They simulate the human brain in the following two ways:

1. A neural network obtains patterns through learning.
2. A neural network's pattern is stored within inter-neuron connection strengths known as synaptic weights.

Neural networks are used to large numbers of worldwide problems. Their prime gain is that they can recognize appropriate patterns for complex problems in comparison to conventional methods. The most common neural network model is the multi-layer perceptron (MLP). This type of neural network is known as a supervised network because it needs a measured output in order to learn. The goal of this type of network is to make a model that properly maps the input to the output using imported data so that the model can then be used to estimate output in case of lack of measurements [25-26]. The tanh-axon transfer function and Levenberg–Marquardt back propagation was used to establish ANN model. By optimization of the model based on the lowest AARD value, the number of hidden neurons in hidden layer was assumed 20.

Input parameters of the ANN model are BSW which expresses the ratio of water rate in total liquid rate, choke size (1/64 in), well head pressure (psi) and CGR, which is condensate to gas ratio (STB/MMSCF). The output parameter is Qg which stands for choke gas flow rate (MMscf/d). In the following, the results of modelling by ANN model are reported. The AARD value of the model is 1.8 %.

LS-SVM is a modified version of SVM and a more simple method than SVM. The LS-SVM allows to handle linear and nonlinear multivariable problems and explains the multivariable problems comparatively fast way to analyze the structure. In this version, one finds the solution by solving a set of linear equations instead of a quadratic programming problem for classical SVMs [27-28]. To achieve optimum values of algorithm parameters (γ and $\sigma2$), the LSSVM model is linked with an optimization approach known coupled simulated annealing (CSA). Having optimized, the values obtained by the CSA-LSSVM algorithm for the estimation of gas flow rates of choke are 0.526941 and 472.5468 for σ^2 and γ, respectively [29]. Input parameters of the LSSVM model are BSW which express the ratio of water rate in total liquid rate, choke size (1/64 in), well head pressure (psi) and CGR, which is condensate to gas ratio (STB/MMscf), as mentioned earlier. The output parameter is Qg which stands for choke gas flow rate (MMscf/d), as mentioned earlier. The AARD value of the model is 1.7 %. Figure 1 illustrates a comparison between the values estimated by DT, ANFIS, LS-SVM, and ANN and the actual data of gas production rate. As clear from the figure, DT has the best performance among all models developed in this study.

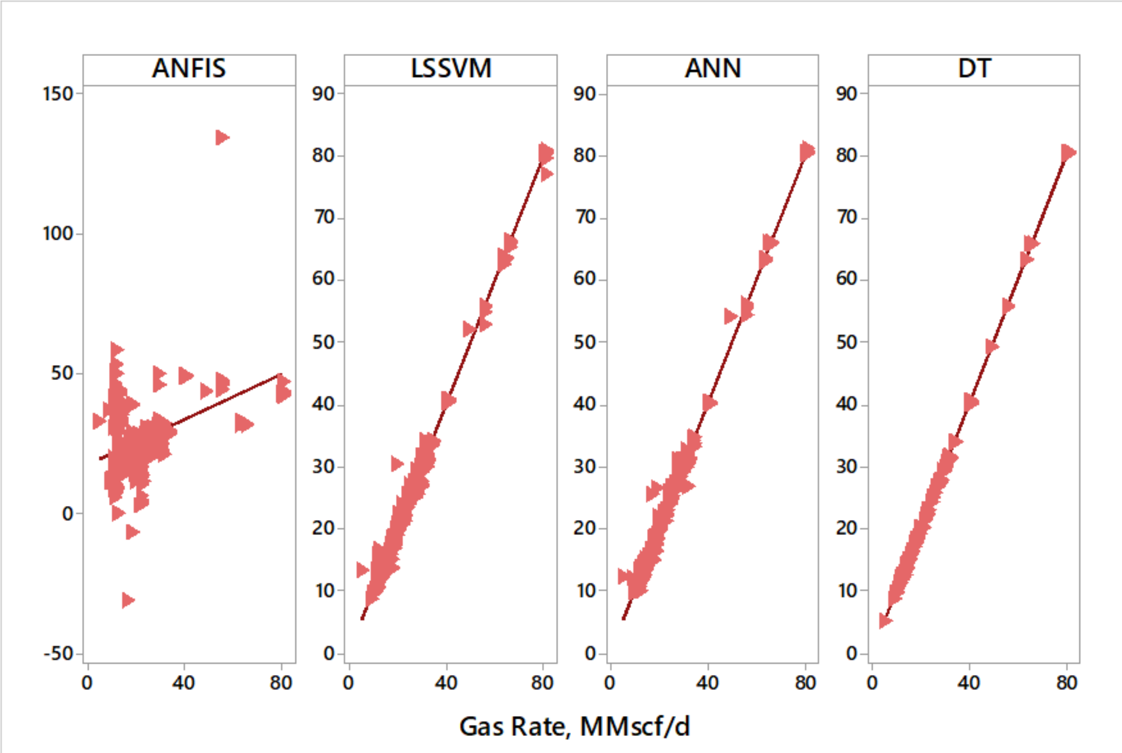

Figure 1. The crossplots for the values etimated by ANFIS, DT, ANN, and LS-SVM models versus the actual data of gas production rate

4. Development of a Model by GEP Approach

As previously pointed out, there is still a necessity to propose reliable methods for estimating gas production rates covering wide ranges of variables. An overview of previously reported studies reveals that BSW, choke Size, CGR and WHP are most effective variables for accurate determination of gas rates from the choke. Therefore, a simple method with four variables is proposed on the basis of gene expression programming in this study for the determination of gas rates from choke for one of Iranian gas condensate reservoirs. It is worthwhile to note that most of previously reported empirically derived correlations do not consider the BSW parameter for developing the model to estimate well choke flow. During development of the method by gene expression programming algorithm, the average absolute relative deviation was considered as an error function to measure the accuracy of the newly proposed model. Furthermore, some simple functions including +, −, /, and log were used to develop the equation. The final form of the method is as follow:

$$Q_g = 0.33217\,BSW + 0.66434\,S + \ln(CGR + WHP) + \frac{47.698\,(BSW + 47.698)(BSW + WHP)^{\frac{1}{3}}}{CGR - WHP} - 3.063 \qquad (5)$$

where Qg stands for choke gas flow rate (MMscf/day), BSW expresses the ratio of water rate in total liquid rate, and S is the choke size (1/64 in), WHP denotes well head pressure (psi), and CGR is condensate to gas ratio (STB/MMSCF).

The results are presented in the following figure. The AARD value of the model is 14 %. Figure 2 indicates the cross plot of the values estimated by the newly proposed method versus the actual data of gas production rate. The results show an acceptable accuracy by applying this method.

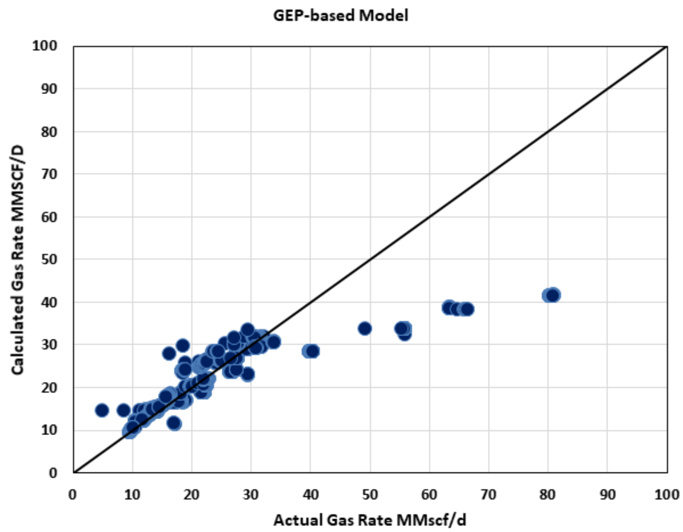

Figure 2. The crossplot for the values predicted by the newly proposed GEP-based method versus the actual data of gas production rate

5. Conclusion

The objective of this study was to find an appropriate modelling approach for choke multiphase flow performance. Three advanced methods were proposed to analyze the data and export reliable patterns to estimate gas flow rate. Besides, a GEP based model was presented to analyze the data. The AARD values for ANN, LSSVM, ANFIS and GEP models are 1.8%, 1.7%, 43% and 14%, respectively. A decision tree with AARD of 0.4 % is the best and accurate technique to estimate gas flow rate in comparison to other approaches. Regarding the model developed by gene expression programming, it shows a good match at low flow rates. Additionally, the accuracy of the GEP based model is decreased with increasing the rate.

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