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Full Length Article

Improved predictions of wellhead choke liquid critical-flow rates: Modelling based on hybrid neural network training learning based optimization

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HIGHLIGHTS

- Robust models for predicting the liquid critical-flow rates for producing oil wells.
- Hybrid artificial neural networks coupled with training learning based optimization.
- Comparing the accuracy of published and new wellhead choke flow rate models.
- Gas/oil specific gravity and temperature impacts on the liquid critical-flow rates.
- Relevancy factors to determine relative contributions of flow rate variables.

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ABSTRACT

Published relationships typically consider liquid critical-flow rate through wellhead chokes of producing oil wells as functions of wellhead pressure, choke size and gas-liquid ratio. Such correlations can be improved by taking into account three additional input variables: gas specific gravity, oil specific gravity and temperature. Novel liquid critical-flow rate models, hybridizing an artificial neural network (ANN) with a teaching-learning-based optimization (TLBO) algorithms, involving 3 and 6 input variables, demonstrate improved accuracy compared to nonlinear regression models, traditional ANN models and published correlations. The improved accuracy of the developed models is assessed statistically using a data set of 113 wellhead flow tests from oil wells in South Iran (with a full data listing included). The ANN-TLBO (6 parameters) developed model is the most accurate, yielding the best liquid critical-flow rate predictions for that data set: coefficient of determination of 0.981; root mean square error of 714; average relative error of 2.09%; and, average absolute relative error of 6.5%. The 6-parameters models outperform the 3-parameters models without over complicating model functionality. This justifies the consideration of all six input variables to deliver improved predictions of wellhead choke liquid critical-flow rates. Calculation of relevancy factors for the 6-parameters ANN-TLBO model to the data set for all six input variables reveals choke size and gas-liquid ratio have maximum and minimum influence in determining the liquid critical-flow rate, respectively.

1. Introduction

In producing oil and gas wells, multiphase flow rate is a key parameters in determining reservoir performance and sustainability [31]. Accurate measurement and exact prediction of fluid flow rates are important for production volume and resource recovery forecasts and for establishing a stable and controllable flow regime in producing wells. Flow rate usually is controlled using chokes

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Nomenclature

A, B, C, D, E and F	empirical constants
ANN	artificial neural network
BP	back propagation
D_{64}	choke size
GLR	gas liquid ratio
G	number of training samples
LSSVM	least square support vector machine
Logsig	log sigmoid
MAPE	mean absolute percentage error
M_i	mean at any iteration i
M_{new}	new mean
m	number of output nodes
Purelin	linear
P_{wh}	wellhead pressure
R	Pearson's correlation coefficient
R^2	coefficient of determination
r_i	a random number in the range of [0, 1]
SD	standard deviation
T	temperature
Tansig	tangent sigmoid
Tsc	standard temperature
T_i	teacher at any iteration i
T_F	teaching factor
TLBO	Teaching-learning-based optimization
Q_L	liquid critical-flow rate
γ_g	gas specific gravity
γ_o	oil specific gravity
ε_i	random errors

which can be set either at the wellhead or downhole. The main purpose of incorporating a choke is to facilitate control over fluid flow rates, but controlling flow through chokes also prevents a number of potential production and reservoir problems, e.g., sand production, water and gas coning, formation damage, stabilizing flow rate and applying back pressure [4,13,26,9,33,34].

Wellhead chokes consists of two main types: fixed and variable, which have different capabilities based on their structural components and designs [7,22]. The fixed-type choke has a fixed (non-adjustable) diameter, while the variable-type chokes allow adjustments to their diameter [5]. Two distinct flow regimes can prevail when passing two phase flow through wellhead chokes: critical (or sonic) flow or sub-critical (or sub-sonic) flow [23,55]. Critical flow occurs when the fluid velocity reaches sonic velocity, which occurs when the. ratio of downstream pressure to upstream pressure is less than 0.588 [42,39]. During this type of flow, the mass flow rate is only a function of the pressure upstream of the choke. Such flow conditions frequently prevail in producing oil and gas wells [29], and are also preferred for some reservoir flooding enhanced oil recovery techniques [54]. It is also applied in other industries, e.g., aerospace [60] and refrigeration engineering [1,19]. Sub-critical flow conditions occur when the mass flow of the fluid is less than the sonic velocity [9]. In sub-critical flow conditions, mass flow rate depends on the pressure drop across any restrictions in the flow stream (e.g., chokes), such that fluctuations in conditions downstream of the restriction combine with upstream conditions to influence flow rates. Critical-flow conditions are usually selected for wellhead chokes in order to achieve stable flow rates and to avoid frequent perturbations in equipment performance.

In the early 1980 s, numerous flow measurement tools were designed and tested in oil and gas wells [32], but they are expensive to implement on a field-wide basis [10]. Therefore, theoretical and analytical approaches provide the predominant approaches used to predict of the flow rate through chokes. Tangren et al. [59] introduced and developed multiphase flow theory applied to restrictions, which forms the foundation of subsequent modelling and analytical studies. Gilbert [20] proposed a correlation and formula (Eq. (1)) for calculating critical flow based on 268 data for choke sizes ranging from 6/18 and 64/64 inches

$$Q_L = \frac{P_{wh} D_{64}^B}{A(GLR)^C} \tag{1}$$

where

P_{wh} is the wellhead pressure (psia),
D_{64} is the choke size (1/64 inch),
GLR is the gas–liquid ratio (SCF/STB), and,
Q_L is the liquid critical-flow rate (STBD).
A, B and *C* are experimental coefficients calculated where sufficient data is available for specific reservoir systems.

Baxendell [8] adjusted Gilbert's equation for critical flow conditions, and Ros [51] proposed an equation to derive oil and gas mass flow rates under critical flow condition. Based on oil well data for the Maracaibo field (Venezuela), Achong [2] established a different set of values for coefficient's A, B and C for Gilbert's equation. Poettmann and Beck [48] improved the performance of Ros's equation using 108 data points for an oil field with choke restrictions varying between 4/64″ and 28/64″. Omana et al. [42] developed a new relationship based on a series of oil/gas two phase flow data with upstream pressure varying between 400 and 1000 psig, liquid flow rate of 800 STBD and choke restriction size varying between 4/64″ and 14/64″.

Fortunati [18] proposed different equations for critical and sub-critical flow regimes, indicating the significance of the boundary between those two flow regimes. Sachdeva et al. [53] developed a theoretically relationship for mixed oil and gas two-phase flow to estimate the magnitude of flow rates through restrictions under critical and sub-critical conditions. Osman and Dokla [43] suggested a relationship for determining flow rates through wellhead restrictions using a least-squares method based on a data series for a gas condensate reservoir. Perkins [46] derived a two-phase flow equation involving mass, momentum and energy balance to express isentropic flow through restrictions.

Guo et al. [25], based on a data set for oil and condensate wells from southwest Louisiana, pointed out that Sachdeva's model is more precise for gas and condensate flow than for oil flow. Beiranvand et al. [9] presented two correlations, one for high-flow rate wells and the other for high water-cut conditions, based on a data set for an oil field offshore Iran. Nejatian et al. [40] applied the le ast-square-support-vector-machine (LSSVM) method for predicting the choke flow coefficient for nozzle and orifice type chokes experiencing sub-sonic natural gas flow conditions. Seidi and Sayahi [55] combined a genetic algorithm with non-linear regression analysis to predict the sub-critical, two-phase flow pressure drop through large-diameter wellhead chokes.

Taking account of the extensive previous research, established relationships and applications involved in modelling and predicting wellhead choke flow, the key objectives of this study is to demonstrate that a novel hybrid analytical approach involving artificial neural networks (ANN) combined with a training -learning-