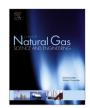
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## A novel PSO-LSSVM model for predicting liquid rate of two phase flow through wellhead chokes



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#### ABSTRACT

Two-phase flow through chokes is common in oil industry. Wellhead chokes regulate and stabilize flow rate to prevent reservoir pressure declining, water coning and protecting downstream facilities against production flocculation. Choke liquid rate prediction is a basic requirement in production scheme and choke design. In this study, for the first time a least square support vector machine (LSSVM) model is developed for predicting liquid flow rate in two-phase flow through wellhead chokes. Particle swarm optimization (PSO) is applied to optimize tuning parameters of LSSVM model. Model inputs include choke upstream pressure, gas liquid ratio (GLR) and choke size which are surface measurable variables. Calculated flow rates from PSO-LSSVM model are excellently consistent with actual measured rates. Moreover, comparison between this model and related empirical correlations show accuracy and superiority of the model. Results of this work indicate PSO-LSSVM model is a powerful technique for predicting liquid rate of chokes in oil industry.

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#### 1. Introduction

Wellhead chokes in oil industry are used to stabilize flow rate, protect the reservoir and surface facilities from pressure swinging and control production rate to prevent water or gas coning (Nasriani and Kalantari, 2011).

Based on bean setting wellhead chokes may be either positive (fixed) or adjustable. In positive choke, bean size is fixed and invariable while adjustable chokes are like variable valves. Due to pressure loss along production tubing and flow line, pressure falls below bubble point and two-phase flow is common in chokes. Flow through wellhead chokes described as either critical or subcritical. Critical flow will occur if velocity is greater than the sonic velocity of the fluid. (Golan and Whitson, 1995; Guo et al., 2007) As a rule of thumb in two phase oil and gas flow, critical flow is established when upstream pressure is at least twice the downstream pressure. The ratio of upstream to downstream pressure is called critical

pressure ratio in which critical flow occurs. If this ratio is greater than or equal to critical pressure ratio critical flow happens otherwise flow is subcritical. In the case of critical, flow rate is independent of downstream noises. As mentioned in critical flow, fluid in choke throat is in its sonic velocity and downstream disturbances such as pressure changes cannot travel faster than sonic velocity, therefore upstream pressure is independent of downstream condition. In critical flow, the flow rate depends on upstream pressure while in subcritical flow pressure difference across choke influence choke flow rate (Guo et al., 2007).

The major problems related to two phase flow through chokes are deriving a relation for calculating the flow rate based on measurable variable such as wellhead pressure, bean size, gas liquid ratio (GLR) and etc. So many researchers have been worked on two phase flow through choke and suggested their correlations. Suggested methods for multiphase flow through chokes are categorized into empirical and analytical (Al-Attar, 2010).

Tangren et al. (1949) accomplished the first endeavor on multiphase flow through restrictions. He added gas bubbles to an incompressible fluid above a critical velocity and showed that medium is incapable of transmitting downstream pressure change

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against the flow direction. The best known multiphase flow choke correlation for critical condition was developed by Gilbert (1954) in which liquid rate is linearly proportional to the upstream pressure. His data include 268 production tests for choke sizes change from 6/64 to 18/64 inch (Tangren et al., 1949; Guo et al., 2007; Safar Beiranvand and Babaei Khorzoughi, 2012). Some researchers like — (Baxendell, 1957), (Ros, 1960) and (Achong, 1961) modified (Gilbert, 1954) equation coefficients and proposed new equations. The general form of Gilbert type equations are as below:

$$Q_{liq} = h \frac{P_{upstream} D^i}{GLR^i} \tag{1}$$

where  $Q_{liq}$ ,  $P_{upstream}$ , D and GLR are liquid rate (STB/D), choke upstream pressure (psi), choke diameter (1/64 in.) and gas liquid ratio (SCF/STB), respectively. h, i and j are Specific coefficients of each equation which are given in Table 1 (Guo et al., 2007).

Ros (1960) extended Tangren's method where gas was continuous phase (Ros, 1960). The work of Ros was improved by Poettmann and Beck (1963). They set some charts up for various crude oils with different API gravity and tested them with 108 production data (Nasriani and Kalantari, 2011; Poettmann and Beck, 1963). Fortunati (1972) established correlations for both critical and subcritical flow through chokes. He also suggested a figure and determined boundary between critical and subcritical flow (Fortunati, 1972). Ashford (1974a) developed a correlation for two-phase critical flow based on Ros works (Ashford, 1974b). Al-Towailib and Al-Marhoun (1994) used 3930 production tests of Middle East fields to expand a new correlation for two phase critical flow through chokes. Their new correlation was similar to Gilbert's equation but they changed GLR term by mixture density and gave better result than previous correlations (Al-Towailib and Al-Marhoun, 1994). Al-Attar (2010) used 40 field tests for developing two equations for critical flow based on bean setting specification then achieved more precise correlation than past proposed ones. He also implemented discharging coefficient and modified Ashford and Pierce (1975) and Fortunati (1972) subcritical correlations by applying 139 field data (Ashford and Pierce, 1975; Al-Attar, 2010). Safar Beiranvand and Babaei Khorzoughi (2012) developed new correlation using 182 data of an Iranian oil field. They added base sediment and water (BS&W) and temperature to Gilbert equation and got more accurate result than prior correlations (Safar Beiranvand and Babaei Khorzoughi, 2012). According to the literature, the most suggested correlations for determining downstream oil flow rate in critical flow through wellhead choke are derived by linear or nonlinear regression methods, which have high error, whereas artificial intelligence techniques are the best alternative for complex problems when adequate data number is available. An artificial intelligent model for single gas flow through choke is proposed in the literature (Nejatian et al., 2014) but no model exists for oil and gas two-phase flow.

In this work for the first time, LSSVM is used for modeling critical two-phase flow through wellhead chokes. LSSVM is a

**Table 1** Specific coefficient for Gilbert type correlation.

Correlation	Specific coefficients		
	h	i	j
Gilbert	0.1	1.89	0.546
Achong	0.262	1.88	0.65
Rose	0.057	2	0.5
Baxendell	0.105	1.93	0.546

kind of intelligent learning machine that modifies drawbacks of support vector machine (SVM) method. LSSVM has parameters that should be set before training model. Finding proper value for these parameters is one of the LSSVM users drudgery. These parameters are tuned by PSO which is a new optimizing algorithm for continuous nonlinear functions (Eberhart and Kennedy, 1995)

#### 2. SVM background

SVM is practical usage of statistical learning theory in multidimensional functions (Vapnik, 1999). It is a learning machine defined for classifying works like optical character recognition (OCR) (Vapnik, 1995) and developed for regression purposes (Drucker et al., 1997; Vapnik et al., 1997). SVM recently used in most engineering fields and proposed models with good accuracy (Esfahani et al., 2015; Meng et al., 2014; Nejatian et al., 2014; Zhou et al., 2011). For simple case input data  $x \in \mathbb{R}^d$  are regressed by hyper plane f(x):

$$f(x) = \langle \omega, x \rangle + b \text{ with } \omega \in X, b \in R$$
 (2)

where  $\langle \omega, x \rangle$  indicates the inner product between x and  $\omega$ . Flat solution will be attained if  $\omega$  is small. In other word its norm  $\|\omega\|^2 = \langle \omega, \omega \rangle$  should be minimum (Safari, 2014). For regression cases Vapnik et al. (1997) defined a loss function as illustrated in Fig. 1 and Eq. (3) which allows some error in specified domain epsilon and some slack variable that could be out of this marginal domain by some penalty (Vapnik et al., 1997).

$$\xi = |y_i - f(\omega, x_i)|$$

$$|\xi|_{\varepsilon} := \begin{cases} 0 & \text{if } |\xi| \le \varepsilon \\ |\xi| - \varepsilon & \text{otherwise} \end{cases}$$
(3)

Loss function definition gives more flexibility to support vector machine regression method. By considering positive slack variables  $(\xi_i, \xi_i^*)$  optimization problem is formulated as bellow:

$$\begin{aligned} & \text{minimize} & & \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{\ell} \left( \xi_i + \xi_i^* \right) \\ & \text{subject to} & \begin{cases} y_i - \langle \omega, x_i \rangle - b \leq \varepsilon + \xi_i \\ \langle \omega, x_i \rangle + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* & \geq 0 \end{cases} \end{aligned}$$

In which C is a positive constant and a penalize factor for the data that their deviation from f are  $\xi_i$  unit higher than  $\epsilon$  (Cherkassky and Ma, 2004; Vapnik, 1998).

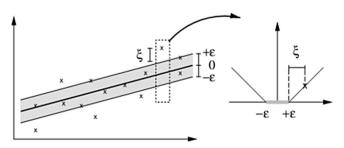


Fig. 1. Vapnik linear loss function (Schölkopf and Smola, 2002).

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