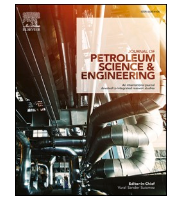
Journal of Petroleum Science and Engineering 208 (2022) 109775

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol



Modelling oil and gas flow rate through chokes: A critical review of extant models

Okorie Ekwe Agwu [a,*], Emmanuel Emeka Okoro [b], Samuel E. Sanni [c]

[a] *Department of Chemical and Petroleum Engineering, University of Uyo, Akwa Ibom State, Nigeria*
[b] *Department of Petroleum Engineering, Covenant University, Ota, Ogun State, Nigeria*
[c] *Department of Chemical Engineering, Covenant University, Ota, Ogun State, Nigeria*

A R T I C L E I N F O

Keywords:
Artificial intelligence
Multiphase flow
Ensemble models
Non-linear regression
Sensors
Wellhead chokes

A B S T R A C T

Oil and gas metering is primarily used as the basis for evaluating the economic viability of oil wells. Owing to the economic implications of oil and gas metering, the subject of oil and gas flow rate measurement has witnessed a sustained interest by the oil and gas community and the academia. To the best of the authors' knowledge, despite the growing number of published articles on this subject, there is yet no comprehensive critical review on it. The objective of this paper is to provide a broad overview of models and modelling techniques applied to the estimation of oil and gas flow rate through chokes while also critically evaluating them. For the sake of simplicity and ease of reference, the outcomes of the review are presented in tables in an integrated and concise manner. The articles for this review were extracted from many subject areas. For the theoretical pieces related to oil and gas flow rate in general, the authors relied heavily upon several key drilling fluid texts. For operational and field studies, the authors relied on conference proceedings from the society of petroleum engineers. These sources were supplemented with articles in peer reviewed journals in order to contextualize the subject in terms of current practices. This review is interspersed with critiques of the models while the areas requiring improvement were also outlined. Findings from the bibliometric analysis indicate that there is no universal model for all flow situations despite the huge efforts in this direction. Furthermore, a broad survey of literature on recent flow models reveals that researchers are gravitating towards the field of artificial intelligence due to the tremendous promises it offers. This review constitutes the first critical compilation on a broad range of models applied to predicting oil and gas flow rates through chokes.

1. Introduction

1.1. Background of the study

Oil and gas metering is an essential factor used as a benchmark to assess the economic viability of oil wells. In addition, knowledge of the flow rates of gas, oil and water from different wells gives operators the basis to make critical decisions that border on optimizing production, flowrates as well as future forecasts of the potential performance of the field (Bikmukhametov and Jäschke, 2020a). However, like all facets of oil and gas exploration and production, measuring accurately the flow of these fluids remains a disturbing challenge both to the production engineer and to those in whose hands the purse strings lie. This is because billions of dollars could be lost if flows are not properly measured. For instance, statistics from the Nigeria Extractive Industries Transparency Initiative (NEITI) show that in 2015, Nigeria had about 9,170,444 million barrels of oil not adequately accounted for due to the oil and gas metering challenge (NEITI, 2015). This challenge is mainly aggravated by the complex nature of the flow of gas, oil and water from the wellbore to the surface.

Due to the recurring nature of this challenge, industry players have proposed unique ways to either eliminate or reduce to the barest minimum the errors associated with oil and gas metering. One of these propositions is the development and use of a *Metering Atlas* (Scheers et al., 2009). Other examples are the Norwegian Handbook for Multiphase flow metering published by the Norwegian Society for Oil and Gas Measurement (NFOGM) and the manual for petroleum measurement standards by the American Petroleum Institute. Oil producing nations on the other hand have come up with unique standards to combat this challenge. This led to the launching of the Extractive Industries

* Corresponding author.
E-mail address: okorieagwu@uniuyo.edu.ng (O.E. Agwu).

https://doi.org/10.1016/j.petrol.2021.109775
Received 8 December 2020; Received in revised form 25 September 2021; Accepted 29 October 2021
Available online 6 November 2021

Transparency Initiative (EITI) in 2003 (Lujala et al.,2017).

Despite these efforts by both the industry and the oil producing nations, the challenge seems to be unabated. Suffice it to say that oil and gas measurement typically occurs at two points during oil and gas production. These points are located at the wellhead and at the custody transfer points. While it is reported that the measurement at the custody transfer point is somewhat seamless usually coming off with a low degree of uncertainty (Scheers et al., 2009), however, a higher degree of uncertainty comes with the measurement done at the wellhead. A typical oil and gas production system highlighting the flow of oil and gas from the reservoir through the wellhead, the choke and then to the test separator is shown in Fig. 1.

Given the complexity in measuring oil and gas flow rates, a number of approaches have been tried and tested by researchers. One of these approaches is the use of predictive models.

During the last seven decades, the oil and gas literature has been diligently paved with series of publications in key journals that project virtually all known means of measuring oil and gas flow rates. In particular, most of the extant literature on the subject of oil and gas metering has been devoted to the development of predictive models. As a result, an appreciable number of mathematical models exist in the oil metering literature. These models have taken various forms ranging from the empirical, theoretical to artificial intelligence based models as well ensemble models. Till date, building a single universal model for oil and gas flow rate prediction has remained elusive because of the high non-linearity effects that emanate from the variation of flow patterns, liquid viscosity and density. However, to the best of the authors' knowledge, despite the availability of a huge number of models for estimating the flowrate of oil and gas, no critique of these models has been done bearing in mind several pertinent acceptable standards. This is gap in literature this work seeks to cover.

1.2. Objective of the study

The specific objective of this work is to curate extant models for predicting fluid flowrates through chokes with the intent of critiquing them by assessing their predictive performances as well as their empirical or mechanistic methodologies while bearing in mind their potential field applications. This is what makes this study novel and serves as its major contribution to the existing body of knowledge on the subject. Finally, potential issues which might be responsible for lack of field applicability of extant prediction models would be isolated and recommendations for future research would be presented.

1.3. Existing approaches to fluid flow rate measurement

There are three distinct and fundamental approaches to multiphase-flow measurements. The first includes fluid separation (using separators), the second uses physical metering devices (use of multiphase flow meters) and the third involves the use of predictive models (virtual flow meters). Production well testing through a test separator is by far the most common practice to measure flow rates (Zangl et al., 2014).

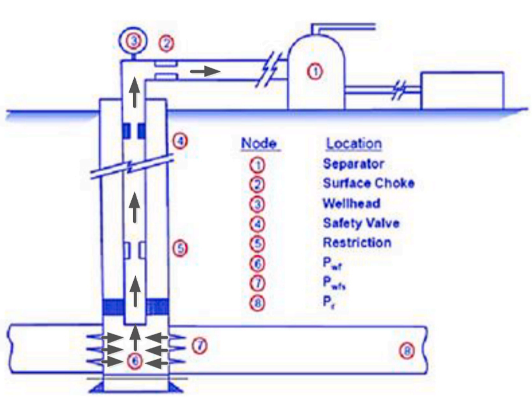


Fig. 1. Schematic of an oil production system and its components.
Source: Mahmud and Abdullah (2017).

Regrettably, even though flow rates of oil, gas and water are the most important parameters of any hydrocarbon exploitation project, only a minor number of wells are permanently connected to a multiphase flow meter (Zangl et al., 2014). However, no single multiphase-flow-measurement system design or technology resolves all multiphase-flow-measurement issues satisfactorily. Each approach has benefits as well as shortcomings. These benefits and shortcomings have been unpacked and curated in the works by Marshall and Thomas (2015) and Bikmukhametov and Jäschke (2020a), however a few are outlined in Table 1.

2. Theory

2.1. Establishing the review sequence

Besides getting knowledge of recent advances, a historical perspective is necessary for important/worthwhile advances in the oil and gas industry (Grigg, 2015). Hence, an in-depth literature review on oil and gas flow rates is necessary. This literature search conducted is predicated on the premise that without a thorough empirically based and theoretical knowledge, one might end up only addressing the symptoms while ignoring the real problems. Hence, this review would take a wholistic approach of isolating historical research efforts in the area of fluid flow rate modelling and extracting the major details of each work with a view to highlighting its main findings and critiquing the models.

Thus, to begin the inquiry, an examination of the existing review works on oil and gas flow rate modelling would take first place. The existing models for fluid flow rate prediction would follow thereafter while a summary of data range used by researchers for fluid flow rate modelling comes next. The major findings by the researchers on fluid flow rate modelling and a critique of these models would follow thereafter while the review finding climaxes the review. Following this sequence would make the work better understood by readers.

2.1.1. Highlights of previous review articles on fluid flow rate modelling through chokes

This section highlights previous review studies on choke flow rate modelling. Three major reviews are available in literature. The focus of each review and the major findings of each review work are presented in Table 2.

It is clear from the above, that though the reviews were comprehensive, they were focused in one direction i.e. mostly on soft computing techniques whereas, techniques such as empirical, theoretical and ensemble modelling techniques abound. A review of studies only from one area of the subject would result in a conclusion that is applicable only to that area in question. On the contrary, a robust review such as the one discussed in this paper which assesses a wide range of modelling methods would provide a new and useful platform where the model user can make informed choices on which method offers the most advantages.

Furthermore, the review this paper presents is a clear departure from the much more common traditional "*review papers*" where the reviewer identifies studies in a particular area, summarizes their findings, and reports a conclusion in narrative form. While useful, such reviews are mainly subjective. This work is not meant to replace the already existing valuable review articles on this subject such as the ones in Table 2, but to provide a complementary perspective with particular focus on critiques of the extant models with the intent to deepen knowledge on the subject; this is what makes this review different from other existing ones in the literature.

Table 1
Challenges of oil and gas flow rate measurement techniques.

Flow rate measurement technique	Pitfalls of measurement technique
Use of test separators	***Cost***: Increased capital cost on field development as a result of a separate flowline and a separator needed to accomplish the test (Falcone et al., 2001) as well as a test line to test separator in satellite fields (Denney, 1998). ***Space requirements:*** The separators and the metering equipment require additional space because of their large footprint and the extra load they impose especially on offshore platforms (Falcone et al., 2009; Mwalyepelo, 2015). ***Errors***: When the test is done using multiphase flow meters, they need to be calibrated using test separator data which often have their inherent uncertainties which lead to errors. The difference in operating conditions of test separators and flow conditions can subsequently add to the errors ***Speed of measurement***: No real time measurement is possible and the process is painfully slow because it takes time for the gas, oil and water to divide in the separator (Corneliussen et al., 2005; Mwalyepelo, 2015; Liu, 2016). Only one well can be tested at a time leading to sparse measurements over the lifetime of a well (Zangl et al., 2014). Since there are no real time measurements, it cannot be used in a feedback system to forestall problems such as slugging or an overdose of chemical injection.
Use of physical multiphase flow meters (MPFM)	***Cost***: Quite expensive in installation and maintenance due to the fact that it has moving parts (Falcone et al., 2001; Patel et al., 2014; Hasanvand and Berneti, 2015). ***Durability***: MPFMs may degrade owing to sand erosion or blockage (Marshall and Thomas, 2015) and may lead to years of inaccurate flow rate measurement if unchecked (Mokhtari and Waltrich, 2016). They also fail to measure flow rates accurately at water cut range of 40–60% or above 90% (Meribout et al., 2010) ***Health & Safety***: Some MPFMs have radioactive sources as detectors which may affect workers (Hasanvand and Berneti, 2015; Roberts and Allen, 1993)
Virtual flow meters (VFM)	***Data requirements***: Lack of sufficient and relevant data due to (i) failure of data measuring devices such as bottom hole pressure (BHP) gauges (ii) non-installation of BHP gauges in some wells (Al-Qutami et al., 2017b) (iii) the inherent uncertainty due to measuring device errors (Khorzoughi et al., 2013) (iv) The gas oil ratio (GOR) of wells are not constants and are subject to change with time but since most VFMs require the expected gas oil ratio (GOR) as inputs, the outputs from the VFMs will be biased when these values change (Petukov et al., 2011) ***Acceptance***: Largely limited by regulatory agencies (Mokhtari and Waltrich, 2016) due to the fact that there is still a scarce number of studies in the literature about VFM model description, validation and field verification (API, 2005). ***Speed of measurement:*** Since VFMs are model dependent, most of the models require fluid properties and production regimes as inputs thus making them have a high computational time (Amin, 2015; Bello et al., 2014).

3. Models for predicting oil and gas flow rate through chokes

The real essence of modelling choke performance is to give petroleum engineers the latitude to optimise the field operating conditions and predict the oil and gas flow rates that can be produced by a given well (Alimonti et al., 2010). Over the past seven decades, an avalanche of models has been developed for flow rate estimation through choke valves. The following are the categories of models for predicting oil and gas flow rate through chokes.

3.1. Theoretical models

Theoretical models are essentially derived from mass, momentum, and energy balances and are used in the oil and gas industry because they can estimate critical and subcritical flow conditions simultaneously under varying flow conditions (Zhibin et al., 2011). In the early 1980s, numerous flow measurement tools were designed and tested in oil and gas wells (Liu et al., 2008), but they were costly to implement on a field-wide basis (Benlizidia, 2009). Therefore, theoretical and analytical models were the predominant methods used then to predict flow rate through chokes. Due to the *slippage effect* that occurs between the gas and liquid phases as a result of density difference (Shao et al., 2018), slip models were developed as part of theoretical models.

A slip model is essentially a correlation used to estimate the relative velocity between two fluid phases (e.g. gas phase and oil phase). Table 3a shows the slip models applied to theoretical models for oil and gas flow rate prediction.

According to Zhou et al. (2018), considerations of slip between the gas and liquid phases at the choke-throat condition appear unimportant for improving a model's performance. This outcome is a direct consequence of the dominance of annular or mist flow in most field settings, wherein the phase slippage appears absent. They cautioned that phase slippage should be used while working with laboratory data involving lower flow rates.

Table 2
Summary of previous review works on flow rate measurement and modelling.

Author (year)	Area covered by review
Williams (1994)	The advantages of multiphase measurement, methods utilized for multiphase measurement to date, research to date, and projected future research
Rastoin et al. (1997)	A review of the performance of three mechanistic models (Ashford and Pierce, 1975; Sachdeva et al., 1986; Perkins, 1990) for predicting multiphase flow rates through wellhead chokes
Oddie and Pearson (2004)	An overview some techniques used for flowrate measurement in two-phase flow
Thorn et al. (2013)	1. Importance of three-phase flow measurement 2. Reason three phase flow measurement problem still persists 3.The extant measurement approaches and a description of the main technologies currently used by commercial manufacturers 4. A review of research developments that could influence the design of future flowmeters
Zhou (2017)	Evaluation of several flow rate models and seven slip models
Buffa and Baliño (2017)	The basic assumptions of two models were reviewed. The models include: Sachdeva et al. (1986) and the model proposed by Al-Safran and Kelkar (2009).
Yan et al. (2018)	A review of the soft computing techniques for multiphase flow metering with a particular focus on the measurement of individual phase flow rates and phase fractions
Zhou et al. (2018)	Evaluated several models and correlations and compared their relative performances and their potential for field applicability
Hansen et al. (2019)	1.Current trends and technologies within multi-phase flow measurements 2. The most promising methods based on accuracy, footprint, safety, maintenance and calibration.
Bikmukhametov and Jäschke (2020a)	Virtual flow meters (VFM)
Meribout et al. (2020)	A critical review on most existing multiphase flow meter technologies
Liu et al. (2020)	A comprehensive evaluation of established correlations for two-phase (gas-liquid) flow through Venturi tubes

Table 3a
Summary of slip models utilized in models for oil and gas flow rate prediction.

Author (s), year	Slip model
$R = a_0\left(\frac{1-x_g}{x_g}\right)^{(a_1-1)}\left(\frac{\rho_L}{\rho_g}\right)^{(a_2+1)}\left(\frac{\mu_L}{\mu_g}\right)^{a_3}$	
Lockhart and Martenelli (1949)	$a_0 = 0.28,\ a_1 = 0.64, a_2 = 0.36, a_3 = 0.07$
Baroczy (1961)	$a_0 = 1,\ a_1 = 0.74, a_2 = 0.65, a_3 = 0.13$
Moody (1965)	$a_0 = 1,\ a_1 = 1, a_2 = -\frac{2}{3}, a_3 = 0$
Henry and Fauske (1971)	$a_0 = 1,\ a_1 = 1, a_2 = -0.5, a_3 = 0$
Simpson *et al.* (1983)	$a_0 = 1,\ a_1 = 1, a_2 = -0.83, a_3 = 0$
Grolmes and Leung (1985)	$a_0 = 1,\ a_1 = 1, a_2 = -0.5, a_3 = 0$
Chisholm (1983)	$S = \left[x_g\frac{v_g}{v_L} + (1-x_g)\right]^{1/2}$
Schuller *et al.* (2006)	$R = \sqrt{1 + x_g\left(\frac{\rho_L}{\rho_g} - 1\right)}\ (1 + 0.6e^{-5x_g})$

Where R = slip factor; S = slip factor; μ_L = liquid viscosity; μ_g = gas viscosity; ρ_L = liquid density; ρ_g = gas density; x_g = gas phase mass fraction; a_0, a_1, a_2, a_3 = dimensionless coefficients; v_L = liquid velocity; v_g = gas velocity.

Table 3b presents a summary of the theoretical correlations for predicting oil and gas flow rate as developed by different authors. The assumptions of the models are also presented. According to Al-Safran and Kelkar (2009), incorporating the slip models in Table 3a into the theoretical models in Table 3b improves the accuracy of their predictions.

3.1.1. Critique of theoretical models

First, since the information and data (experimental or field) varies with respect to the variables to be modelled, the assumptions made, the inflexible nature of the theoretical procedures, most theoretical models fail in accurate prediction of flow rate. Second, the calculations involved with theoretical models are intensive and have a high burden which ultimately gulps a lot of time to execute.

3.2. Empirical models or Gilbert type models

In recent decades, researchers have presented many models for predicting oil and gas flow rates through wellhead chokes. The earliest known empirical correlation for critical flow is that of Gilbert (1954). Table 4 presents a snapshot of the various researches from which oil and gas flow rates were modelled. For ease of reference, the summary is presented in a tabular form beginning from the earliest study and terminating with the latest study. Each row of the table corresponds to one of the models. Each column corresponds to a vital information about the developed model.

The following can be gleaned from the summary. First, a total of 47 models were extracted from literature. There were huge similarities in the input parameters, the modelling technique and the area from which the data were obtained. In most of the cases, the input variables were wellhead pressure, gas liquid ratio and choke size. However, by developing models that consider not only the impact of only these three inputs but also additional inputs such as gas specific gravity, oil specific gravity and temperature, its accuracy in flow rate prediction can be significantly improved (Choubineh et al., 2017). It was also observed that the area where the data were obtained was predominantly in the Middle East region. Furthermore, while some researchers did not document the size of the dataset they utilized, the largest dataset used contained 3354 data points and the smallest dataset had 27 data points and the majority of the models were for critical flow. Finally, the modelling technique that was widely used was the non-linear regression method. The theoretical description of this method is presented as follows:

3.2.1. Overview of non-linear regression

Regression models are the conventionally used statistical techniques for establishing the relationship (either linear or non-linear) existing between two or more variables that represent any phenomena. A simple linear regression describes the relationship between two variables (e.g. x and y) with a straight line ($y = mx + c$); while non-linear regression describes the relationship between the two variables in a non-linear or curved manner (Kenton, 2020). A brief description of two common regression models is given as follows:

(i) *Multiple Linear Regression (MLR)*: MLR simply known as multiple regression is an expanded form of simple linear regression used for modelling the linear relationship between several independent variables and a dependent variable (Chapra and Canale, 2010). Essentially, MLR is the broadening of the ordinary least squares regression since it requires more than one independent variable (Hayes, 2021). An MLR model is expressed mathematically as shown in Equation (1).

$$y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots \beta_p x_p + \in \quad (1)$$

Where y is the dependent variable; $x_1, x_2, \ldots\ldots\ldots x_p$ are the independent variables; $\beta_1,\ \beta_2 \ldots \beta_p$ are estimates of the linear regression and $\in$ is the random error term (James et al., 2013)

(ii) Multiple Non Linear Regression (MNLR): MNLR is essentially a form of MLR analysis in which data are modelled by a function that is a non-linear amalgamation of the parameters of the model. Just as MLR, MNLR is dependent on one or more predictor/independent variables. Whereas MLR is commonly used for developing simple models, MNLR is mainly adopted when it is observed (from a physical standpoint) that the relationship between the independent and dependent variables mirrors a specific functional form. Mathematically, the general form of a MNLR model is as shown in Equation (2).

$$y = \beta_0\left(x_1^{\beta_1}\right)\left(x_2^{\beta_2}\right)\ldots\ldots\left(x_n^{\beta_n}\right) \quad (2)$$

Where β_0, β_1, ...,β_n are regression parameters to a set of a number of tabulated values of the independent variables: $x_1, x_2, \ldots\ldots\ldots x_n$; and y is the dependent variable (Bilgili and Sahin, 2010). Non-linear regression utilises trigonometric functions, exponential functions, Gaussian functions, power functions, logarithmic functions, Lorenz curves etc. (Kenton, 2020). In order to obtain the regression constants of a MNLR model, series of iterations are involved. Methods such as Newton-Raphson method, Gauss-Newton method, Levenberg-Marquardt method, quadratic hill climbing method and method of scoring etc. are often utilized (Donthi et al., 2019). For a more comprehensive coverage on regression models, the work by James et al. (2013) is recommended.

3.2.2. Parameter ranges used in empirical models for oil and gas flow rate prediction

Table 5 is a summary of the range of the parameters used in the modeling of fluid flow rate as isolated from literature. It is evident that the important parameters are: (1) wellhead pressure, (2) GOR, (3) API gravity (4) choke size, (5) gas liquid ratio, (6) temperature while flow rate was the output parameter. Wherever information is not indicated, it means that no actual reporting was made by the relevant reference. From an inspection of the list, it is evident that there is no consensus on the input parameters required for modeling fluid flow rate. While most studies considered three input parameters (wellhead pressure, choke size and GOR), others included parameters such as water cut, BS&W, API gravity and gas liquid ratio. The widest range of wellhead temperature was in the study by Nasriani et al. (2019) wherein the temperature ranges from 191 to 463 °F, while the least range was 60–120 °F as given by Abdul-Majeed (1988). For all wellhead pressure ranges, the highest [1400–12000 psia] was that given by Beiranvand et al. (2012), while the least [60–350 psia] was by Ganat and Hrairi (2018). For choke size range, the highest [37–192(1/64 inch)] was by Nasriani et al. (2019),

Table 3b
Summary of theoretical models for oil and gas flow rate prediction.

Author(s), year	Mass flow rate model and areas of application
Fortunati (1972)	$q_o^0 = \frac{F_t(1-\beta)}{B_o} C_v V \left(\sqrt{\frac{P_2}{P_1}}\right)^k$ $q_0^o = \frac{P_2 F_t}{\sqrt{GOR(\rho_o^o + \rho_g^o R_{s1})\frac{P_0 ZT}{T_O}}}$ q_o^o = Liquid rate at standard conditions; Ft = total cross sectional area of the choke passage; Bo = oil formation volume factor; GOR = gas oil ratio; T = temperature; P_2 = downstream pressure; P_1 = upstream pressure; k = ratio of specific heat; ρ_o^o = oil density at standard conditions; ρ_g^o = gas density at standard conditions; Po = Pressure at standard conditions, To = temperature at standard conditions; Z = gas compressibility factor; V = mixture velocity; R_{si} = Total gas in solution; C_V = cumulative discharge coefficient; (1 – β) = liquid concentration in respect to the mixture Application: Model can be used for critical and subcritical flow parameter estimation.
Ashford (1974)	$Q_m^2 = 2g_c A_2^2 P_1 144 \frac{\frac{Rk}{k-1}(1-y^{(k-1)/k}) + (1-y)}{V_L^*[1+Ry^{-1/k}]^2}$ Where Q_m = mixture flow rate; R = slip ratio; k = ratio of specific heat; y = pressure ratio; A = Total cross sectional area; P_1 = upstream pressure, g_c = gravitational constant; V_L = liquid velocity
Fahim *et al.* (1978)	$Q_o = \frac{\pi C_o d^2}{4\beta_o}\left[\frac{2g_cP_1}{\rho_o}\left(1-\frac{P_2}{P_1}\right)\right]^{\frac{1}{2}}(1-\alpha_g)$ $Q_g = \frac{\pi T_{sc} P_1 C_g d^2 \alpha_g}{4\beta_o Z T_1}\left[\frac{2g_cP_1k}{\rho_{g1}(k-1)}\left(1-\frac{P_2}{P_1}\right)^{\frac{k-1}{k}}\right]^{\frac{1}{2}}$ Where Q_o = oil flow rate; Qg = gas flow rate; g_c = gravitational constant; P_1 = Upstream pressure; P_2 = Downstream pressure; α_g = gas phase fraction; B_o = oil formation volume factor; ρ_o = oil density; d = choke diameter; C_o = oil compressibility; π = 3.142; Z = gas deviation factor; k = ratio of specific heat; T_1 = working temperature; ρ_g = gas density; T_{SC} = Temperature at standard conditions; C_g = gas compressibility
Sachdeva *et al.* (1986)	$Q_m^2 = C_D\left\{2g_c * 144 P_1\rho_{m2}^2\left[\frac{(1-x_1)(1-y)}{\rho_L} + \frac{x_1 k}{k-1}(V_{G1} - yV_{G2})\right]\right\}^{0.5}$ Where Q_m = mass flow rate; k = ratio of specific heat; P_1 = Upstream pressure; V_{G1} = Specific volume of gas at upstream conditions; V_{G2} = Specific volume of gas at downstream conditions; ρ_m = mixture density; x_1 = phase fraction of liquid; ρ_L = liquid density; g_c = gravitational constant; C_D = Discharge coefficient; y = downstream to upstream pressure ratio Application: Can be used for critical and subcritical flow parameter estimation
Perkins (1993)	$w_i = A_2\rho_2V_2 = \frac{A_2V_2}{\left[f_g v_2 + \left(\frac{f_o}{\rho_o}\right) + \frac{f_w}{\rho_w}\right]}$ Where $V_2 = \sqrt{\frac{288g_c\{\lambda P_1 v_1[1-P_r^{(n-1)/n}] + [(f_o/\rho_o)+(f_w/\rho_w)]P_1(1-P_r)\}}{1-\left(\frac{A_2}{A_1}\right)^2[(f_g+\alpha_1)/(f_gP_r^{-1/n}+\alpha_1)]^2}}$ Where w_i = mass flow rate; g_c = 32.2 (lbm-ft)/(lbf second^2); P_1 = Upstream pressure; P_r = Downstream pressure to upstream pressure ratio; A_2 = Area of choke throat (ft^2); A_1 = Area of choke at upstream (ft^2); f_g, f_o, f_w = weight fraction of gas, oil and water respectively in the flowing stream; ρ_g, ρ_o, ρ_w = density of gas, oil and water respectively; v_1 = Specific volume of liquid; n = polytropic expansion exponent; $\alpha = \left(\frac{1}{v}\right)\left(\frac{f_o}{\rho_o}+\frac{f_w}{\rho_w}\right)$; $\lambda = f_g + \left[\frac{(f_gC_{vg}+f_oC_{vo}+f_wC_{vw})M}{zR}\right]$; M = molecular weight; R = Universal gas constant; z = gas compressibility factor; C_{vo}, C_{vw}, C_{vg} = heat capacity of oil, water and gas respectively
Al-Safran and Kelkar (2009)	$m^2 = \frac{CA_2^2p_1\left[\alpha(1-r)+\frac{n}{n-1}\left(1-r^{\frac{n-1}{n}}\right)\right]}{x_g v_{g1}(r^{-1/k}+\alpha)^2\left[x_g+\frac{1}{R}(1-x_g)\right]}$ Where m = mass flow rate; n = polytropic gas expansion exponent; k = gas specific heat ratio; R = slip ratio; x_g = gas quality; r = pressure ratio; v_{g1} = gas specific volume; A = choke cross sectional area; P_1 = Upstream pressure; v_L = liquid specific volume; C = constant = $2000C_D^2$; C_D = discharge coefficient; $\alpha = \frac{R(1-x_g)V_L}{x_gv_{g1}}$ Utilized the Schuller et al. (2006) slip model for critical flow and the Grolmes and Leung (1985) model for subcritical flow
Mwalyepelo and Stanko (2016)	$m = C_DA_2\left\{2\rho_{m2}^2P_1\left(x_g+\left(\frac{1-x_g}{R}\right)\right)\left[\left(R(1-x_g)v_1(1-y)+\frac{kx_g}{k-1}(v_{g1}-yv_{g2})\right)\right]\right\}^{0.5}$ Where m = mass flow rate (kg/sec); C_D = discharge coefficient; A = total cross sectional area (m^2); ρ_m = mixture density; P_1 = Upstream pressure; x_g = mass fraction of gas; k = ratio of specific heat; R = slip ratio; v_1 = specific volume of liquid; y = ratio of downstream pressure to upstream pressure; v_{g1} = specific volume of gas upstream; v_{g2} = specific volume of gas downstream This model utilized the Grolmes and Leung (1985) slip model. Application: Can be used for critical and subcritical mass flow rates
Shao *et al.* (2018)	$m_c = C_dm_a$ $m_a^2 = (\rho_{m2}A_2V_2)^2 = \frac{2P_1A_2^2[\lambda(y^{1-1/k}-1)+S\alpha(y-1)]}{v_{g1}*\left[x_g+\frac{1}{S}(x_w+x_o)\right]*[r^2(x_g+S\alpha)^2-(x_gy^{-1/k}+S\alpha)]}$ Where m_a = adiabatic mass flow rate; ρ_m = mixture density; S = slip ratio; A_2 = Area at choke throat; y = ratio of pressure at choke throat to the pressure upstream; x_g, x_o, x_w = weight fraction of gas, oil and water respectively; k = ratio of specific heat; $\alpha = \frac{1}{v_{g1}} * \left(\frac{x_w}{\rho_w}+\frac{x_o}{\rho_o}\right)$; $\lambda = x_g + \frac{x_gC_{vg}}{ZR_g} = x_g\left[k+\frac{1}{Z(k-1)}\right]$; r = ratio of area at choke throat to area at upstream; v_{g1} = specific volume of gas at upstream; C_d = discharge coefficient;; R_g = Gas constant, 8.314 J/mol K; Z = gas compressibility factor; C_{vg} = specific heat value of gas at constant volume condition, kJ/(kg·K)

(*continued on next page*)

Table 3b (*continued*)

Author(s), year	Mass flow rate model and areas of application
	This model utilized the Schuller et al. (2006) slip model Application: Can be utilized for critical and subcritical mass flow rates

while the least [4–14(1/64 inch)] was by Omana et al. (1968). The most used parameters were choke size, wellhead pressure, wellhead temperature and GOR while the least used parameters were water cut and BS&W.

3.2.3. Findings on empirical modelling of oil and gas flow rate

This section summarizes the major findings by diverse researchers on the outcomes of the models they developed using the empirical modelling technique. The summary is presented in Table 6 starting with the earliest model. 95% of the findings indicate that the empirical modelling technique limits the model to the range of data used in developing it. A few modifications were observed to have been done to the model by Gilbert (1954). These modifications were in the form of inclusions of new variables such as BS&W, water cut, bottomhole temperature, pay zone depth and tubing size. There is a seeming unanimity amongst researchers, that incorporating new variables such as BS&W and tubing size improves the models' accuracies while variables such as water cut and bottom hole temperature diminished the models' accuracies.

3.2.4. Critique of the empirical models

3.2.4.1. Model flexibility. A model's flexibility is defined as the amount of influence data features has on the behaviour of a model (Johnson, 2017). The critique against the usefulness of Gilbert type models is linked to the elements causing inflexibility in the models. The cause of the inflexibility is as a result of the fixed analytic form of the Gilbert type model. It is fair to say that in most of the contributions by researchers in developing the Gilbert type models, the emphasis has been on the modification of Gilbert's model rather than charting a new course. There is little difference between the models in terms of the novelty of their contributions.

3.2.4.2. (ii) replicability of Model's results. The determination of the explicit form of a regression equation is the ultimate objective of regression analysis. Obtaining the estimates of the model's parameters involves an iterative process. Without the numerical coefficients of these parameter and/or the associated constants, the model would limit its usefulness. Some models in Table 4 failed to meet this objective. An example is the multiple linear regression model by Zangl et al. (2014). This model was without the regression coefficients hence this would limit the usefulness, applicability and replicability of the results of the model.

In summary, going through the models in Table 4, a common and perhaps universal factor amongst the models is the striking resemblance of the models with little or no new contributions to knowledge arising from the fact that they are mainly modifications of the Gilbert's model. These pitfalls most likely propelled the search for newer modelling approaches such as artificial intelligence. The next section highlights the various models put forward by diverse researchers for estimating oil and gas flow rate using the disruptive technology of artificial intelligence.

3.3. Artificial intelligence based models

The last few years have seen the introduction of supervised machine learning algorithms as tools to exploit data for the purpose of modelling oil and gas flow rate. With data available, machine-learning has been used to capture potentially complex relationships between oil and gas flow rate and the factors affecting it. These approaches can largely be divided into: ANN, SVM, Fuzzy logic, Hybrid models etc. The review this section presents would serve as a robust framework that unites all the individual studies on artificial intelligence (AI) models for flow rate prediction into a single piece. For quicker reference and to make the review simplified and unambiguous, the salient details of each study are presented in tables. A snapshot of this summary is shown in Table 7. This table chronicles from the earliest to the latest the research outputs on modelling oil and gas flow rates using artificial intelligence techniques as put forward by different researchers.

In a bid to make the summary detailed, the method used by each researcher is highlighted; the data source and the number of data points, the input parameters as well as the correlation developed by each researcher where applicable are also mentioned. A total of 49 papers were extracted from extant literature relating to this. While it is apparent that various researchers used different input parameter combinations to model oil and gas flow rate through chokes (e.g. wellhead pressure, gas oil ratio, choke size, oil API, oil water ratio, basic sediments and water, wellhead temperature etc.), it is clear from Table 7 that wellhead pressure, gas oil ratio and choke size are the most widely used input parameters. In terms of data size, there was a wide variability in the size of data points used by the researchers. As large as 17097 data points were used by one researcher and as low as 67 was used by another. Most of the models were developed for fields in the Middle East region.

From the summary, it is observed that in the last decade, most AI based models on estimating oil and gas flow rate revolved mainly around the use of artificial neural networks where about 60% of studies reviewed pointing to this fact. ANN models are currently, and are expected to remain the choice for simulating critical and subcritical flows in oil and gas production systems, owing to their computational tractability; however, they suffer from poor accuracy and predictive power in some cases. In terms of model performance using statistical error metrics, it was observed that the models were elegant however due to the fact that the number of data points, the modelling technique, the number and type of input parameters varied widely, there is no sound basis of comparing their performances. A brief description of the artificial intelligence modelling techniques is presented in the next section.

3.3.1. Overview of AI methods applied to the prediction of oil and gas flow rate

3.3.1.1. Artificial neural network. Artificial neural networks (ANN) are essentially bio-inspired computational systems that are designed to learn and utilize the knowledge gained to estimate the outputs of a complex system. The basic unit of a neural network is the neuron. These neurons are connected together to form a network capable of solving a complex problem (Behnoud far and Hosseini, 2017). An ANN comprises three layers namely: the input layer, the hidden and the output layer. The input layer neurons represents the number of input parameters to the network. The hidden layer neurons are tasked with the responsibility of feature extraction. The manner in which ANN processes information is as follows: First, each of the inputs (I_1, I_2, I_3) are assigned connection weights (w). These inputs are then multiplied by their individual connection weights. The weighted sum of the inputs and connection weights are then combined and a bias term (b) is added to the summation. The essence of the bias is to either increase or decrease the input that goes into the activation function. The summation is passed through a transfer or activation function, and the output is then computed and transferred to another neuron. Sigmoid transfer function and linear activation function (purelin) are recommended for the hidden and

Table 4
Summary of researches on oil and gas flow rate prediction using empirical methods.

Authors	Method/Data size & source	Input Parameters	Correlation developed
Gilbert (1954)	Non-linear regression 268 production datasets from Kern County oil fields of California	Wellhead pressure, gas oil ratio and choke diameter	$Q_o = \frac{P_{wh}.D_{64}^{0.546}}{10(GLR)^{1.89}}$ Where Q_o = Oil flow rate (STB/D); D = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio (SCF/STB)
Baxendell (1958)	Non-linear regression Venezuelan oilfields	Wellhead pressure, gas oil ratio and choke diameter	$Q_o = \frac{P_{wh}.D_{64}^{0.564}}{9.56(GLR)^{1.93}}$ Where Q_o = Oil flow rate (STB/D); D = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio (SCF/STB)
Ros (1960)	Non-linear regression	Wellhead pressure, gas oil ratio and choke diameter	$Q_o = \frac{P_{wh}.D_{64}^{0.5}}{17.4(GLR)^{2}}$ Where Q_o = Oil flow rate (STB/D); D = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio (SCF/STB)
Achong (1961)	Non-linear regression	Wellhead pressure, gas oil ratio and choke diameter	$Q_o = \frac{P_{wh}.D_{64}^{0.65}}{3.82(GLR)^{1.88}}$ Where Q_o = Oil flow rate (STB/D); D = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio (SCF/STB)
Poettmann and Beck (1963)	Non-linear regression 108 data points	Water oil ratio, specific gravities of oil, gas and water, liquid density, pressure, discharge coefficient, Choke area, mixture density, specific volume of liquid, molecular weight of liquid	$Q_o = \frac{86400C_DA_c}{\rho_m}\sqrt{\frac{9273.6P}{V_L(1+0.5M_L)}} * \frac{0.4513(R+0.766)^{0.5}}{R+0.5663}$ Where $M = 350\gamma_O + 0.0764\gamma_g R + 350\gamma_w(WOR)$; $R = [0.00504T_1Z_1(GLR - R_{S1})]/P_1B_{O1}$ $M_L = 1/[1 + R(\rho_{g1}/\rho_{L1})]$; $V_L = M_L/\rho_{L1}$ Where Q_o = Oil flow rate; WOR=Water oil ratio; γ_g, γ_o, γ_w = specific gravities of gas, oil and water respectively; ρ_L = liquid density; P = pressure, C_D = discharge coefficient, A = Choke area, ρ_m = mixture density; v_L = specific volume of liquid; M_L = Liquid molecular weight; GLR = gas liquid ratio; B_o = Oil formation volume factor; T = temperature; Z = gas compressibility factor; R_{s1} = Solution gas liquid ratio at upstream conditions; ρ_g = gas density
Nind (1964)	Not reported	Wellhead pressure, gas oil ratio and choke diameter	$Q = \frac{P_1 d^2}{600R^{0.5}}$ Where Q = Flow rate (STB/D); d = choke size (1/64 in); P_1 = Wellhead pressure (psi); R = gas liquid ratio (SCF/STB)
Omana et al. (1969)	Multiple regression /Experimental tests in the Tiger Lagoon field of Louisiana with natural gas and Water	Upstream pressure, gas liquid ratio, and choke size	$N_{ql} = 0.263N_\rho^{-3.49}N_{pl}^{3.19}Q_d^{0.67}N_d^{1.8}$ (i) $N_{ql} = 1.84Q_L(\rho_L/\sigma)^{1.25}$; (ii) $N_\rho = c/\rho_L$; (iii) $N_{pl} = \frac{0.0174P_{us}}{\sqrt{\rho_L\sigma}}$ (iv) $Q_d = 1/(1+R_s)$; (v) $N_d = 0.01574D_{64}\sqrt{\rho_L\sigma}$ Where N_{ql} = liquid flow rate number; N_d = diameter number; N_p = upstream pressure number; Q_d = gas/liquid ratio number; σ = surface tension; P_{us} = Upstream pressure (psi); ρ_L = liquid density; D_{64} = Choke diameter (1/64 in); R_s = Solution gas liquid ratio (SCF/STB)
Ashford (1974)	Not available 27 data points	Gas oil ratio, water oil ratio, wellhead pressure, choke diameter,	$Q_o = \frac{1.53C_DD_c^2P_1}{(B_o+WOR)^{0.5}} * \frac{\{[T_1Z_1(GOR-R_{s1})+151P_1](\gamma_o+0.000217\gamma_gR_{s1}+WOR\gamma_w)\}^{0.5}}{[T_1Z_1(GOR-R_{s1})+111P_1](\gamma_o+0.000217\gamma_gGOR+WOR\gamma_w)}$ Where WOR=Water oil ratio; γ_g, γ_o, γ_w = specific gravities of gas, oil and water respectively; ρ_L = liquid density; P = pressure, C_D = discharge coefficient, D_c = choke diameter, GOR = gas oil ratio; B_o = Oil formation volume factor; T = working temperature; Z = gas compressibility factor; R_{s1} = Solution gas liquid ratio at upstream conditions
Akbar (1978)	Multiple regression	Upstream pressure, gas liquid ratio and PVT properties, and choke size	$Q = 4.4939 * 10^{-3}P_fS^2$ $Q = 3.6495 * 10^{-3}P_fS^2$ Where Q = flow rate (STB/D); S = choke size (1/64 in); P_f = flowing wellhead pressure (psi)
Pilehvari (1981)	Linear Regression 168 data points obtained from Experimental tests	Upstream pressure, gas liquid ratio, and choke size	$p_1 = \frac{46.666q_LR_p^{0.313}}{d^{2.111}}$ P_1 = Upstream pressure (psi); q_L = liquid flow rate (STB/D); R_p = producing gas oil ratio(SCF/STB); d = choke diameter (1/64 in.)
Abdul-Majeed (1988)	Non-Linear Multiple Regression 155 tests in the East Baghdad fields	Upstream pressure, gas liquid ratio, and choke size	$N_{ql} = 272N_\rho^{-0.2357}N_p^{0.6357}Q_d^{0.61505}N_d^{1.6704}$ *for* $D < 6/64''$ $N_{ql} = 197.6N_\rho^{-0.3797}N_p^{0.5916}Q_d^{0.61648}N_d^{1.7042}$ *for* $6/64 \le D < 10/64''$ $N_{ql} = 321.837N_\rho^{-0.07955}N_p^{0.37395}Q_d^{0.5928}N_d^{2.0072}$ *for* $10/64 \le D < 30/64''$ $Q = (19 + 1.53D + 0.83D^2)(-1.8059 + 0.033755P - 8.657 * 10^{-6}P^2)API^{0.31}G^{-0.52}$ Where D = choke diameter (1/64 in); N_d = diameter number; N_L = liquid viscosity number; N_{qL} = liquid volume rate number; N_ρ = Density or mass ratio number; R = volumetric gas liquid ratio (SCF/STB); Q_d = dimensionless production number; P = pressure (psi); G = producing gas liquid ratio (SCF/STB); API = Oil API gravity; N_{PL} = Upstream pressure number
Al-Attar and Abdul-Majeed (1988)	Non-Linear Multiple Regression East Baghdad oil field	Upstream pressure, gas liquid ratio, and choke size	$Q_o = 0.33567D^{1.796}P^{0.8756}R^{-0.2693}API^{-0.43957}$ where: Qo = oil flow rate (STB/D); D = choke diameter (1/64 in); P = wellhead pressure (psi); R = gas oil ratio (SCF/STB); API = American Petroleum Institute oil gravity
Surbey et al. (1989)	Non-linear regression /Experimental data collected for a high-pressure air/water system	Pressure, choke area, gas oil ratio	$q_L = \frac{P_1A_c^{0.4664}}{0.16549849R_p^{0.3955}}$ P_1 = Upstream pressure (psi); q_L = liquid flow rate (STB/D); R_p = producing gas oil ratio (SCF/STB); A_c = choke cross sectional area (ft^2)

(*continued on next page*)

Table 4 (*continued*)

Authors	Method/Data size & source	Input Parameters	Correlation developed
Osman and Dokla (1990)	Least squares method /87 data points form 8 wells producing from a gas condensate reservoir in the Middle East	Upstream pressure, gas liquid ratio, and choke size	$P_1 = 829 Q_L GLR^{0.4344} / S^{1.8478}$ $P_1 = 767 Q_g LGR^{0.5598} / S^{1.8298}$ $\Delta P = 310.01 Q_L GLR^{0.5919} / S^{1.8626}$ $\Delta P = 302 Q_g LGR^{0.4038} / S^{1.8587}$ Where Q_L = liquid flow rate (STB/D); S = choke size (1/64 in); P_1 = Upstream pressure (psi); GLR = gas liquid ratio(SCF/STB); LGR = liquid gas ratio(SCF/STB); Q_g = Gas flow rate (MMSCF/D)
Abdul-Majeed and Maha (1991).	Non-Linear Multiple Regression 210 data points	Upstream wellhead pressure, GLR, choke size, Oil API gravity, Upstream temperature, Gas specific gravity	$Q = (19 + 1.53D + 0.83D^2)(-1.8059 + 0.033755P - 8.657 * 10^{-6}P^2)API^{0.31}G^{-0.52}$ Where Q = flow rate (STB/D); D = choke diameter (1/64 in); P = pressure (psig); G = producing gas liquid ratio, (SCF/STB); API = Oil API gravity
Al-Towailib and Al-Marhoun (1994)	Nonlinear multiple regression 3554 production test data from ten fields in the Middle East	Choke size (s), upstream wellhead pressure (P_{us}), oil relative density (γ_o), gas relative density (γ_g), gas oil ratio (R_p), mixture relative density (γ_m)	$Q_o = \frac{1.886 * 10^{-3} D^{2.07} P^{0.981}}{(\gamma_o + 2.18 * 10^{-4} R \gamma_g)^{1.464}}$ Where Qo = oil flow rate (STB/D); D = choke diameter (1/64 in); P = pressure (psig); γ_g, γ_o = specific gravity of gas and oil respectively; R = producing gas liquid ratio (SCF/STB)
Elgibaly and Nashawi (1998)	Least squares method 154 (critical flow) 106 (Subcritical flow) Data points/Iraq, UAE and Kuwait, Ashford and Pierce paper	Pressure drop (ΔP), gas liquid ratio (R) and choke size (D).	$Q = \left[\frac{1204.8913 D^{2.747}}{R_p^{1.13501}} \Delta P\right]^{\frac{1}{2}}$ [*Subcritical flow*] $Q = \frac{0.612 D^{1.62}}{R_p^{0.677}} P$ [*Critical flow*] Where Q = flow rate (STB/D); D = choke diameter (1/64 in); P = pressure (psig); R_p = producing gas liquid ratio, (SCF/STB)
Mesallati et al. (2000)	Non-Linear Multiple Regression/62 data points (vertical wells) and 73 data points (horizontal wells), Bouri oil field	Flowing wellhead pressure, gas liquid ratio, and surface wellhead choke size.	$Q_L = 0.0564 P_{wh}^{1.6785} GLR^{-0.0947} DC^{1.431}$ [*for vertical wells*] $Q_L = 1389.65 P_{wh}^{-0.565} GLR^{-0.00172} DC^{1.132}$ [*for horizontal wells*] Where Q_L = liquid flow rate (STB/D); DC = choke diameter (1/64 in); Pwh = well head pressure (psig); GLR = gas liquid ratio (SCF/STB)
Ghareeb and Shedid (2007)	Least squares method solved using Gaussian elimination 1750 data points from 352 producing wells in Egypt.	Wellhead temperature, bottom hole temperature, tubing cross-sectional area, producing gas/oil ratio, water cut	$Q = \frac{9.2x10^{-4} T_{th}^{3.27} H^{1.2} A^{0.81} GOR^{0.041}}{T_{bh}^{1.2} WC^{0.046}}$ Where Q = flow rate (STB/D); T_{th} = wellhead temperature(°F); T_{bh} = bottomhole temperature (°F); A = tubing cross sectional area; WC = water cut (%); GOR = gas oil ratio (SCF/STB); H = well producing depth (ft)
Al-Rumah and Bizanti (2007)	Regression analysis 621 data points from 63 vertical oil wells, Sabriyah field in Kuwait	Flowing wellhead pressure, gas liquid ratio, and surface wellhead choke size.	$q_L = \frac{P_{wh}^{0.96614} d_c^{1.946479}}{188 R_{GL}^{0.06322}}$ Where Q_L = liquid flow rate; d_c = choke size, 1/64 in; P_{wh} = Wellhead pressure, psi; GLR = gas liquid ratio
Al-Attar (2008)	Non linear regression/ 97 data points from 3 gas condensate wells, Middle East	Pressure drop (ΔP), gas liquid ratio (R) and choke size (S).	$Q_g = (1/29653.3)\Delta P S^{1.15537} R^{0.84695}$ [subcritical flow] Where Q_g = gas flow rate (MMSCF/D); S = choke size (1/64 in); ΔP = Pressure drop (psi); R = gas liquid ratio (SCF/STB)
Al-Attar (2009)	Regression analysis 40 field tests for critical flow conditions and 139 field tests for subcritical flow conditions all in the Middle East	Gas liquid ratio, choke size, upstream pressure	Cameron LD $Q_L = 4.543 * 10^{-3} P_1 (GLR - R_{S1})^{0.04921} D_C^{1.7523}$ [subcritical flow]; $Q_L = 1.262 * 10^{-3} P_1 (GLR)^{0.2470} D_C^{1.733}$ Cameron F $Q_L = 9.454 * 10^{-5} P_1 (GLR - R_{S1})^{0.79110} D_C^{1.7358}$; $Q_L = 1.801 * 10^{-1} P_1 (GLR)^{-0.64} D_C^{1.972}$ Bean Setting $Q_L = 2.03 * 10^{-3} P_1 (GLR - R_{S1})^{0.14930} D_C^{1.837}$; $Q_L = 2.18 * 10^{-3} P_1 (GLR)^{0.0897} D_C^{1.879}$ Where Q_L = liquid flow rate (STB/D); R_{s1} = Solution gas liquid ratio at upstream conditions (SCF/STB); GLR = gas liquid ratio (SCF/STB); D_c = choke diameter (1/64 in); P_1 = Upstream pressure (psi)
Nasriani and Kalantari Asl (2011).	Non linear regression 61 data points From 15 wells in 10 different fields	Choke size (S), Pressure drop (ΔP), gas liquid ratio (R)	$Q_g = \frac{S^{1.9}}{9350 R^{-0.65}} \Delta P$ Where Q_g = gas flow rate(MMSCF/D); S = choke size (1/64 in); ΔP = Pressure drop(psi); R = gas liquid ratio (SCF/STB)
Beiranvand and Khorzoughi (2012)	Non linear regression 182 data points	Wellhead pressure, gas liquid ratio, choke size, basic sediments and water, temperature	$Q = \frac{P_{wh}^{0.5} S^{1.5} \left(1 - \frac{BS\&W}{100}\right) \left(\frac{T}{T_{sc}}\right)^{-0.8}}{GOR^{0.1}}$ Where Q = flow rate (STB/D); S = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GOR = gas oil ratio (SCF/STB); BS&W = basic sediments and water (%); T = working temperature (°F); T_{sc} = Temperature at standard conditions (°F)
Beiranvand et al. (2012)	Levenberg-Marquardt algorithm 748 data points Offshore field in Iran	Wellhead pressure, gas liquid ratio, choke size, basic sediments and water	$Q_o = \frac{P_{wh} . D_{64}^{0.586}}{30.49 (GLR)^{2.275}}$; $Q = 0.0382 \frac{P_{wh} S^{2.151} \left(1 - \frac{BS\&W}{100}\right)^{0.5297}}{GLR^{0.5154}}$ Where Q = flow rate (STB/D); D_{64} = S = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio (SCF/STB); BS&W = basic sediments and water (%)

(*continued on next page*)

Table 4 (*continued*)

Authors	Method/Data size & source	Input Parameters	Correlation developed
Sadiq (2012)	Nonlinear multiple regression analysis Iraqi oil wells	Choke upstream pressure, choke size, producing gas to liquid ratio.	$Q = 19049.65P^{-0.69}D^{0.704}GOR^{0.101}$ Where Q = flow rate (STB/D); D = choke size (1/64 in); P= Pressure (psi); GOR = gas oil ratio (SCF/STB)
Mirzaei-Paiaman (2013).	Nonlinear multiple regression analysis/51 data points from 17 gas condensate wells in 7 Iranian fields	Choke upstream pressure, choke size, and producing gas to liquid ratio.	$Q_L = \frac{0.615744P_{wh}d^{1.83}}{GLR^{0.736}}$ Where Q_L = Liquid flow rate(STB/D); d = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio(SCF/STB)
Khorzoughi et al. (2013)	Non-linear method of Nelder–Mead and Linear regression 182 production tests in a southern offshore field in Iran	GLR, Choke size (S), Wellhead pressure, Temperature, BS&W	$\ln(Q) = -4.0285568 + 0.56\ln(P_{wh}) + 1.94\ln(S) + 0.73\ln\left(1 - \frac{BS\&W}{100}\right) + 6.82\,ln\left(\frac{T}{T_{sc}}\right) + 0.047\ln\ (GLR)$ Where Q = flow rate (STB/D); S = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio (SCF/STB); BS&W = basic sediments and water (%); T = working temperature(°F); T_{sc} = Temperature at standard conditions (°F)
Mirzaei-Paiaman and Salavati (2013)	Non-linear multiple regression analysis/124 data points from 15 Persian oil fields	Choke upstream pressure, choke size, gas oil ratio (GOR)	$Q_o = \frac{0.087607P_{wh}d^{1.9215}}{GOR^{0.5334}}$ Where Q_o = Oil flow rate (STB/D); d = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GOR = gas oil ratio (SCF/STB)
Zangl et al. (2014)	ANN, Multiple linear regression & Random forest classification 258 data points	Tubing head pressure, tubing head temperature, gas lift rate, gas lift injection pressure, flowline pressure	Not stated
Bairamzadeh and Ghanaatpisheh (2015)	Non linear regression 1300 data points from 120 Iranian offshore oil wells	Upstream wellhead pressure, gas liquid ratio, choke size	$Q_l = \frac{P_{wh}^{0.9383} * D_{choke}^{1.7137}}{7.8337GLR^{0.3636}}$ Where Q_l = liquid flow rate (STB/D); D_{choke} = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio (SCF/STB))
Obukohwo et al. (2015)	Not reported	Not reported	$Q_O = \frac{(1 - W_{ct}) * MF * 4.1085}{\gamma_{ml} * B_{ot}} + \frac{(1 - G_{ft}) * MF * 4.1085}{B_{ot} * \gamma_{ml}}$; $Q_{gs} = \frac{G_{ft} * MF * 23.0676}{B_{ot} * \gamma_{mg}}$ Where Q_o = oil flow rate (STB/D); Q_{gs} = gas flow rate (MMSCF/D); γ_{ml} , γ_{mg} = specific gravity of oil and water, specific gravity of gas and any oil carry over at test conditions; MF = mass flow rate; W_{ct} = water cut(%); B_{ot} = oil formation volume factor; G_{ft} = gas formation volume factor
Seidi and Sayahi (2015)	Non-linear regression 67 data sets from South Iranian gas condensate reservoirs	Choke size, Gas Liquid ratio, pressure drop across choke	$Q_g = \frac{0.015S^{1.27}\Delta P^{0.56}}{(LGR)^{0.4}}$ Where Q_g = gas flow rate(MMSCF/D); S = choke size (1/64 in); ΔP = Pressure drop (psi); LGR = liquid gas ratio (SCF/STB)
Bokhamseen et al. (2015)	Generalized reduced gradient (GRG2) non-linear algorithm/64 data points from 16 separator tests	Choke diameter, upstream pressure, upstream temperature, gas specific gravity, gas and condensate rates and GOR	$q_g = \frac{P_{up}d^{1.85}}{59.88CGR^{0.11}}$; $q_g = \frac{0.211d^{1.92}P_{up}}{\sqrt{\gamma_g(T_{up} + 460)}}$ Where Q_g = gas flow rate (MMSCF/D); d = choke size (1/64 in); P_{up} = Upstream pressure(psi); CGR = condensate gas ratio; T_{up} = Upstream temperature(°F); γ_g = gas specific gravity
Nasriani and Kalantari Asl, (2015)	Non-linear regression/ 64 data points from 15 high rate wells located in Iran	Choke size (S), Pressure drop, gas liquid ratio	$Q_g = (1\ /6868169.43)\Delta PS^{2.25544}R^{0.750342}$; Where Q_g = gas flow rate (MMSCF/D); S = choke size (1/64 in); ΔP = Pressure drop(psi); R = gas liquid ratio (SCF/STB)
Okon et al. (2015)	Multivariate regression/64 data points Niger Delta (Nigeria) oil wells	Wellhead pressure, gas liquid ratio, choke size, flowing temperature, basic sediments and water	$P_{wh} = \frac{5.1474(GLR^{0.5048})q}{S^{1.7098}}$ $P_{wh} = \left[\frac{19.65(GLR^{0.6749})q}{S^{1.8133}\left(1 - \frac{BS\&W}{100}\right)^{0.2235}\left(\frac{T}{T_{SC}}\right)^{0.000029}}\right]^{0.757}$ Where q = flow rate (STB/D); S = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio (SCF/STB); BS&W = basic sediments and water(%); T = working temperature(°F); T_{sc} = Temperature at standard conditions (°F)
Lak et al. (2017)	Multivariate regression/864 data points From Persian Gulf offshore	Wellhead pressure and temperature, choke diameter, separator pressure and temperature	$P_{wh} = \frac{0.25T_{wh}^{k}R^{0.899}q_l}{S^{1.76}}$ Where q_l = liquid flow rate(STB/D); S = choke size (1/64 in); P_{wh} = wellhead pressure(psi); R = gas liquid ratio(SCF/STB); T_{wh} = Wellhead temperature (°F)
Choubineh et al. (2017)	Non-linear regression/ 113 data points from 12 South Iran oil wells	Well head pressure, choke size, oil specific gravity, gas specific gravity, temperature, gas liquid ratio	$Q_L = \frac{0.067662\,x\,P_{wh} * D_{64}^{2.08918} * \gamma_g^{0.625862} * \gamma_o^{1.583074} * \left(\frac{T}{T_{sc}}\right)^{0.000453}}{GLR^{0.508714}}$ $Q_L = \frac{0.059094 * P_{wh} * D_{64}^{2.101865}}{GLR^{0.560742}}$ Where Q_L = liquid flow rate(STB/D); D_{64} = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); GLR = gas liquid ratio(SCF/STB); T = working temperature(°F); T_{sc} = Temperature at standard conditions(°F); γ_g = gas specific gravity; γ_o = oil specific gravity
Ganat and Hrairi (2018)	Non-linear regression 96 data points from North African oil wells	Wellhead temperature, bubble point pressure (pb), producing gas-oil ratio, WHP, overall shut in time (t), and water cut	$Q_O = 0.002236(WHP_a - WHP_b)^{0.976949}WHT^{1.013912}t^{-0.97168}GOR^{0.634736}(100 - WC)^{1}pb^{0.011189}$ Where Qo = oil flow rate (STB/D); WHP = wellhead pressure (psi); WHT = wellhead temperature (°F); GOR = gas oil ratio (SCF/STB); WC = water cut (%)

(*continued on next page*)

Table 4 (*continued*)

Authors	Method/Data size & source	Input Parameters	Correlation developed
Fuladgar and Vatani (2019)	Multi variable linear regression/142 data sets from South West Iran	Wellhead pressure, choke size and producing gas liquid ratio	$Q = \frac{0.3135 P_{wh}^{.807949} C_s^{1.740565}}{R^{0.407676}}$; Where Q = flow rate (STB/D); C_S = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); R = gas liquid ratio (SCF/STB)
Nasriani et al. (2019)	Non-linear regression/ 234 production data points	Liquid gas ratio, choke size (S) and the pressure drop across the choke	$Q_g = \frac{0.0437 S^{1.1136} \Delta P^{0.4836}}{(LGR)^{0.3129}}$; Where Q_g = gas flow rate (MMSCF/D); S = choke size (1/64 in); ΔP = Pressure drop(psi); LGR = liquid gas ratio (SCF/STB)
Al-Rumah and Alenezi (2019)	Non-linear regression/ 835 data points	Liquid gas ratio (RGL), choke size (d) and the pressure drop across the choke (Pwh), API gravity	$q_L = \frac{P_{wh}^{0.91772} d_c^{2.0346} API^{1.104824}}{249.8503 R_{GL}^{0.61029}}$ $q_L = \frac{P_{wh}^{0.848836} d_c^{1.883216}}{3.337139 R_{GL}^{0.553744}}$; Where q_L = liquid flow rate (STB/D); d_c = choke size (1/64 in); P_{wh} = Wellhead pressure (psi); RGL = gas liquid ratio(SCF/STB); API = oil API gravity
Jumaah (2019)	Non linear regression/ 33 production tests data from 12 wells produce from Tertiary Reservoir in Khabaz oil field	Gas oil ratio (GOR), choke size (D), Flowing wellhead pressure (Pwf), water cut	$Q = PWF \frac{D^{0.000275}}{1.7634 GOR^{0.9058}}$ $Q = PWF \frac{D^{0.0000486}}{1.733 GOR^{1.159}} * \left(1 - \frac{Wct}{100}\right)^{1.3936}$ Where Q = flow rate (STB/D); Wct = water cut (%); GOR = gas oil ratio(SCF/STB); PWF = flowing wellhead pressure (psi); D = choke diameter (1/64 in)
Kargarpour (2019)	Semi analytical approach/399 data points	Oil API gravity (SpGr), Upstream choke pressure (P_1), GOR, Choke size (d), downstream choke pressure (P_2)	$q_{BPD} = P_1 d^2 * \left\{ \frac{\sqrt{P_1}}{552 * \sqrt{\frac{\left(1 - \frac{P_2}{P_1}\right)}{SpGr}}} + \frac{GOR}{65554 * \sqrt{\left(\frac{P_2}{P_1}\right)^{1.5625} \left[1 - \left(\frac{P_2}{P_1}\right)^{0.21875}\right]}} \right\}^{-1}$ Where q_{BPD} = well flow rate (STB/D); P_1 = upstream choke pressure (psi); GOR = gas oil ratio (SCF/STB); d = choke diameter (1/64 in); P_2 = downstream choke pressure (psi); SpGr = liquid specific gravity with respect to water

Table 5
Summary of range of data used by researchers on the use of empirical techniques in modelling oil and gas through chokes.

Author(s), Year	Flow rate (STB/D)	Wellhead pressure (psia)	API gravity	GOR (SCF/STB)	Water cut (%)	Choke size (1/64 inch)	Gas liquid ratio (SCF/STB)	Wellhead Temperature (°F)	BS&W (%)
Gilbert (1954)			25–40			6–18			
Omana et al. (1968)	800	400–1000				4–14			
Abdul-Majeed (1988)	10.5–4728	100–4374	17–56.3			4–40	102–18594	60–120	
Surbey et al. (1989)	450–3550	85–950				27–90	140–5200	48–132	
Al-Towailib and Al-Marhoun (1994)	172–33847	97–1880	27–40	12–5026		16–160		160–240	
Elgibaly and Nashawi (1998)	31–6501	180–5100	26–58	127–12163.3	0–92.3	5.9–72		105–170	
Al-Rumah and Bizanti (2007)	45–6900	120–1400				16–91	17–1900		
Al-Attar (2008)	260–1917					24–128		155–180	
Nasriani and Kalantari Asl (2011)	9.30–110.35 MMSCF/D	1131–4452				40–192	51–1453	113–200	
Beiranvand and Khorzoughi (2012)	183–9284	133–883		36–885		25.6–40		87.6–162	0.1–53
Beiranvand et al. (2012)	3000–24000	1400–12000				16–40	80–260		0.1–30
Mirzaei-Paiaman (2013).	266.3–5706	832–8410				24–128	1743–51300		
Mirzaei-Paiaman and Salavati (2013)	198–9643	115–4308	22.97–43	158–20324		16–128			
Bokhamseen et al. (2015)	3–26 MMSCF/D	1500–4500		2500–3500		16–72		140–230	
Nasriani and Kalantari Asl, (2015)	9.3–110.35	1131–4452				40–192	51–1453	113–200	
Okon et al. (2015)	263–5313	36–2320				16–76	93–4134	100–150	0–0.884
Bairamzadeh and Ghanaatpisheh (2015)	110–11200	103–1120				12–92	12–30782		
Lak et al. (2017)	281–2520	1580–4180				24–64	13900–43300	95–151	
Ganat and Hrairi (2018)	200–3350	60–350	30–40	300–1100	0–98	16–64			
Fuladgar and Vatani (2019)	100,000	200–4000	19–34	290–1670		12–52		205–271	
Nasriani et al. (2019)	5.4–113.3	14.5–2104				32–192	0.69–178.8	191.93–463.73	
Kargarpour (2019)		38–5538	12.8–42	61–6044		8–96			
Al-Rumah and Alenezi (2019)	10.5–6892	85–4374	11–56				102–18579		
Jumaah (2019)	400–2900	445–1854			0–4.7	16–42	847–2595		

Table 6
Summary of findings by researchers on the use of empirical techniques in modelling critical flow rate of oil well fluids.

Author(s), Year	Method used	Major findings and conclusions
Ashford (1974)		The discharge coefficient necessary to predict rate of production ranges between 0.642 and 1.218.
Akbar (1978)	Multiple linear regression	Production data that is accurate is required to obtain an average of the flow rates of oil and gas.
Abdul-Majeed (1988)	Non-linear regression	The rate of production predicted by the original and modified forms of the Omana model is not strongly related to the viscosity of oil.
Surbey et al. (1989)	Non-linear regression	The model is limited to only multi-orifice-valve (MOV) chokes.
Osman and Dokla (1990)		The model developed is most accurate when pressure drop data is used instead of choke upstream pressure.
Al-Towailib and Al-Marhoun (1994)	Non-linear regression	Taking into account the mixture density in oil and gas flow rate models is necessary.
Elgibaly and Nashawi (1996)	Least squares method	The developed model is used for critical flow rate prediction and requires PVT data.
Ghareeb and Shedid (2007)	Least squares method solved using Gaussian elimination	The accuracy of the model's prediction is linked to its taking into account other variables that were not accounted for by the Gilbert model such as size of tubing, depth of payzone and wellhead temperature.
Al-Attar (2009)	Regression analysis	For critical and subcritical flow conditions, the model developed outperformed extant models. Data on water cut are required for developing models for these conditions.
Nasriani and Kalantari Asl (2011)	Non-linear regression	The range to which the developed model can be applied is as follows: choke size: 40–192 (1/64 in), GLR: 51–1453 MSCF/STB, Wellhead flowing temperature: 113–200 °F, Upstream pressure: 1131–4452 psi, Downstream pressure: 825–3045 psi.
Beiranvand and Khorzoughi (2012)	Non-linear regression	Basic sediments and water (BS&W) and temperature are important variables that significantly affect flow rate prediction and therefore should be accounted for when developing flow rate models.
Beiranvand et al. (2012)	Non linear regression	BS&W is an important variable that significantly affect oil and gas flow rate prediction.
Mirzaei-Paiaman (2013)	Nonlinear multiple regression analysis	Since a wide range of data was utilized in developing the model, it can be applied to many fields around the world.
Mirzaei-Paiaman and Salavati (2013)	Nonlinear multiple regression analysis	The developed model is less complex than existing models making it more convenient for use. Since a wide range of data was utilized in developing the model, it can be applied to many fields around the world.
Khorzoughi et al.(2013)	Non-linear method of Nelder–Mead and Linear regression	Incorporating BS&W and temperature in the developed models improved its accuracy.
Zangl et al. (2014)	Linear regression, ANN, Random Forest classification	Of the three modelling techniques, the model developed using ANN had a higher predictive accuracy than the others followed by the random forest classification and then the linear regression model
Okon et al. (2015)	Multivariate regression analysis	The models can be used to predict oil production rate in fields in the Niger Delta area of Nigeria
Bairamzadeh and Ghanaatpisheh (2015)	Non-linear regression analysis	The developed model outperformed those of Gilbert (1954), Ros (1960), Achong (1961) and Baxendell (1958).
Moghaddasi et al. (2015)	Not stated	In comparison with the models proposed by Gilbert (1954), Ros (1961), Baxendell (1958), Achong (1961), Pilehvari (1981) the Baxendell (1958) model captured more accurately the dynamics of the data from 14 wells from the Asmari reservoir located in southwest Iran.
Lak et al. (2017)	Multivariate regression	Uncertainty in the flow rate of water diminishes the regression's accuracy.
Ganat and Hrairi (2018)	Non-linear regression	The developed model is quick, reliable, and can be adapted to any ESP oil well as well as artificially onshore and offshore flowing wells but can only be applied to critical flow conditions.
Fuladgar and Vatani (2019)	Multi variable linear regression	An evaluation of the new correlation indicated that it could significantly improve accuracy of flowrate predictions in contrast to previous prominent correlations
Nasriani et al. (2019)	Non-linear regression	This model works best when applied within the range of the following production parameters: LGR of 0.7–178.8 bbl/MMscf, a choke size: 24/64 to 192/64, gas flow rate of 5.4–113.3 MMscfD.

output layers respectively (Mekanik et al., 2013). This process is depicted in Fig. 2.

The first step in modelling with ANN is the training of the network. Data are processed through the input layer to the hidden layer(s) then all the way to the output layer. In the output layer, the predicted data are compared with the actual data. The difference between actual and predicted data is transferred back to the model to update the individual weights between each connection and the biases of each layer. This process is called epoch. In this way, training continues for all the dataset until the average error reduce to certain defined limit (Demuth et al., 2009). Network performance also depends upon the number of neurons in the hidden layer, fewer neurons cause under-fitting and excessive neurons cause over-fitting, so optimization is required for the designing of neurons (Aalst et al., 2010; Haykin, 1999). The overall correlation between inputs and output for an ANN model is as shown in Equation (3) (Fazeli et al., 2013).

$$y_k = f_o\left[\sum_j w_{kj}.f_h\left(\sum_i w_{ji}x_i + b_j\right) + b_k\right] \quad (3)$$

Where x is an input vector; w_{ij} represents the weight from the ith neuron in the input layer to the jth in the hidden layer; b_j represents the bias of jth hidden neuron; w_{kj} represents the weight from the jth neuron in the hidden layer to the kth neuron in the output layer; b_k represents the bias of kth output neuron and f_h and f_o are the activation functions for the hidden and output neuron respectively. The following are the types of ANN: (i) Modular Neural Networks (ii) Feedforward backpropagation Neural Network (iii) Radial basis function (RBF) Neural Network (iv) Kohonen Self Organizing Neural Network (v). Recurrent Neural Network (RNN) (vi) Convolutional Neural Network (CNN) (vii) Long/Short Term Memory (viii) Multilayer perceptron (MLP) (ix) Deep neural network

3.3.1.2. Fuzzy logic. Fuzzy logic by definition is an accurate computational system which has the capability to interpret and represent information that is vague, incomplete, uncertain, imprecise, ambiguous or partially true (Zadeh, 2009; Yadav and Singh, 2011). The fuzzy logic system has the ability to capture the non-linear relationship of an input-output model without an exact mathematical formula (Liu and Li, 2005). Modelling with fuzzy logic entails utilizing a linguistic approach (descriptive language) established on fuzzy logic with fuzzy propositions (Adeyemi et al., 2016). The operational mechanism of fuzzy logic is to map an input space (universe of discourse) to an output space, using a list of *"if then"* statements referred to as rules (Castillo and Melin, 2001). Thus, a fuzzy model can be viewed as an assemblage of various linear models implemented locally in the fuzzy regions described by the rule premises with the final model being represented by the intermediate or interpolation of the linear models (Lima et al., 2015). According to Kayacan and Khanesar (2016), fuzzy logic system is carried out in four basic steps namely: input data fuzzification, fuzzy rules evaluation, aggregation of outputs of fuzzy rules and output defuzzification.

3.3.1.3. Hybrid intelligent systems. A technique that results from the amalgam of two or more methods is called a hybrid. In artificial

Table 7
Summary of critical and subcritical flow models based on artificial intelligence.

Authors	Method/ Architecture	Data size/source	Inputs and Output Parameters	Performance metrics
ZareNezhad and Aminian (2011)	ANN [3–30 – 1]	97 data points	Inputs: Pressure drop (psi), gas-to-liquid ratios (SCF/STB), choke size (1/64 in.) Output: Gas flow rate (MMSCF/D)	$R^2 = 0.9996$; RMSE = 0.26; AARE (%) = 0.486
Berneti and Shahbazian, (2011).	ANN and Imperialist Competitive Algorithm (ICA) [2–7 – 1]	31 wells in Iran	Inputs: Temperature (°F), pressure (psi) Output: Oil flow rate (STB/D)	$R^2 = 0.9703$; MSE = 0.0123
Al-Shammari (2011)	ANFIS	796 data points Middle East	Inputs: Flowing wellhead pressure (psi), liquid rate, water cut (%), gas oil ratio (SCF/STB), oil API, reservoir temperature (°F), tubing inside diameter (in.), gauge depth (ft) Output: Flowing pressure at gauge depth (psi)	$R^2 = 0.93$; AARE (%) = 4.93
Al-Khalifa and Al-Marhoun (2013)	ANN [6–9 – 5–8 – 1]	4031 data points	Inputs: Upstream wellhead pressure (psi), temperature (°F), choke size (1/64 in.), oil and gas relative densities (γo and γg), production GOR (SCF/STB) Output: Liquid critical flow rate (STB/D)	R = 0.986; RMSE = 10.5; APE = 0.4; AAPE = 6.7
Ahmadi et al. (2013)	i. ANN ii. Fuzzy Logic iii. ANN-ICA	1600 data set of 50 wells in Iran	Inputs: Temperature (°F), pressure (psi) Output: Oil flow rate (STB/D)	ANN: $R^2 =$ 0.93909; MSE = 0.091343 Fuzzy logic: R^2 = 0.9037; MSE = 0.0073664 ANN-ICA: $R^2 =$ 0.99505; MSE = 0.0030392
Nejatian et al. (2014)	Least-Squares Support Vector Machine (LSSVM)	171 (orifice) 164 (nozzle) data points	Inputs: Reynolds number, d/D (ratio of choke diameter to pipe diameter) Output: Choke flow coefficient	Orifice: $R^2 =$ 0.9993; RMSE = 0.0016; AARE = 0.1881 Nozzle: $R^2 =$ 0.9955; RMSE = 0.0038; AARE = 0.2529
Bello et al. (2014)	Hybrid intelligence system	Data from literature	Inputs: Flowing bottom hole pressures (psi), flowing bottomhole temperatures (°F), tubing pressures (psi), tubing temperatures(°F), choke opening position, gas oil ratio (SCF/STB), oil water ratio, API gravity Output: Oil and gas flow rates (STB/D; MMSCF/D)	Not reported
Kaydani et al. (2014)	Genetic programming	200 data points	Inputs: Upstream wellhead pressure (P) (psi), gas oil ratio (GOR)(SCF/STB), and surface wellhead choke size (D) (1/64 in.) $q = 1000 * \left[9.59 * 10^{-5}\frac{P_u * \left(\frac{D}{2500}\right)^2}{GOR} + \frac{0.0254 * D}{2500}\right]$ (Critical flow) $q = 1000\left[\frac{3.447 * 10^{-7}}{0.975}\frac{\left(\frac{\Delta P}{100}\right)^2 * \left(\frac{D}{2500}\right)^3}{\left(\frac{GOR}{1000}\right)} * \sqrt{\frac{0.145 * \Delta P}{100} + \frac{0.0254 * D}{2500} + \frac{GOR}{1000}}\right]^{1/4}$ (Subcritical flow) Output: Liquid critical flow rate & Liquid subcritical flow rate (STB/D)	Critical flow: R^2 = 0.988; RMSE = 0.006, AARE = 0.102 Subcritical flow: $R^2 = 0.90$; RMSE = 0.014; AARE = 0.155
Zangl et al. (2014)	ANN	258 data points	Inputs: Tubing head pressure (psi), tubing head temperature (°F), gas lift rate, gas lift injection pressure, flowline pressure (psi) Outputs: Liquid rate, Water rate, Oil rate (STB/D)	Liquid rate: $R^2 =$ 0.9706 Water rate: $R^2 =$ 0.9706 Oil rate: $R^2 =$ 0.9308
Al-Ajmi et al. (2015)	ANN	174 data points	Inputs: Well head pressure (psi), choke size (1/64 in.), temperature (°F), gas oil ratio (SCF/STB), water cut,($P_{upstream}$ T.S/GLR), Gilbert correlation, gas liquid ratio Output: Liquid critical flow rate (STB/D)	$R^2 = 0.89$, MAPE = 15.15
Hasanvand and Berneti (2015)	ANN [2–7 – 1]	600 datasets (31 wells)Iran	Inputs: Temperatures (°F) and pressures of lines (psi) Output: Oil critical flow rate (STB/D)	$R^2 = 0.98741$; RMSE = 0.09746
Al-Ajmi et al. (2015)	ANN	421 data points	Inputs: $P_{upstream}$, $P_{downstream}/P_{upstream}$, temperature/$P_{upstream}$, $\Delta P/P_{upstream}$, water cut, GOR. WC, gas liquid ratio (SCF/STB), Log (S), 1/log (choke size) Output: Liquid subcritical flow rate (STB/D)	$R^2 = 0.93$; MAPE = 15.7
Seidi and Sayahi (2015)	Genetic algorithm	67 data sets Iranian gas reservoirs	Inputs: Choke size (1/64 in), Gas Liquid ratio (SCF/STB), pressure drop across choke (psi) Output: Gas condensate subcritical flow rate	$R^2 = 0.9189$; RMSE = 7.655
Elhaj et al. (2015)	ANN Fuzzy logic SVM Functional Network Decision Tree	162 data points from a field in Sudan	Inputs: Choke size (1/64 in.), Upstream tubing pressure (psi), downstream tubing pressure (psi), upstream tubing temperature (°F), gas gravity Output: Gas flow rate (MMSCF/D)	ANN: $R^2 =$ 0.99986; AARE (%) = 0.828133 Fuzzy logic: AARE (%) = 0.681219 SVM: AARE (%)

(continued on next page)

Table 7 (*continued*)

Authors	Method/ Architecture	Data size/source	Inputs and Output Parameters	Performance metrics
				= 1.662585 Functional network: AARE (%) = 4 Decision tree: AARE (%) = 0.836
Zareiforoush et al. (2015)	ANN [6–17 – 1]	399 data points	Inputs: Wellhead pressure (psi), Wellhead temperature (°F), Choke size (1/64 in), Specific gravity of gas, specific gravity of oil, basic sediments and water Output: Wet Factor	Not reported
Ghadam and Kamali (2015).	Comparative Neural Fuzzy Inference System	84 data points	Inputs: Temperature (°F), produced gas density, rate of produced liquids, ratio of liquid to gas (SCF/STB), apparent velocity of gas, and apparent velocity of liquid Output: Gas critical flow rate (MMSCF/D)	R^2 = 1; MAE = 0.0466
Gorjaei et al. (2015)	PSO-LSSVM	276 data points, Iran	Inputs: Choke upstream pressure (psi), gas liquid ratio (SCF/STB) and choke size (1/64 in.) Output: Oil flow rate (STB/D)	R^2 = 0.9935; AARE (%) = 0.7
Okon and Appah (2016)	ANN i. [3–6 – 5–1 – 1] ii. [5–6 – 6–1 – 1]	64 data points, Nigeria	Inputs: Flowing wellhead pressure (psi), choke size (1/64 in.), gas-liquid ratio (SCF/STB), flowing temperature (°F) and basic sediments and water (BS&W) Output: Oil critical flow rate (STB/D)	i. R^2 = 0.9653; RMSE = 0.365; AARE (%) = 0.192 ii. R^2 = 0.9951; RMSE = 0.4533; AARE (%) = 0.1045
Naseri et al., (2017)	ANN (GA-RBF)	308 (nozzle) 243 (orifice) datasets.	Inputs: Ratio of choke diameter to the pipe diameter (d/D), Reynolds number Output: Choke flow performance	R^2 = 0.999695; RMSE = 0.003755; AARE = 0.339991
Baghban et al. (2016)	Support Vector Machines (SVM)	100 data points, Iran	Inputs: Wellhead pressure (psi), gas oil ratio (SCF/STB), diameter of choke (1/64 in.) Output: Liquid flow rate (STB/D)	R^2 = 0.9998
Choubineh et al. (2017)	ANN-TLBO [6–10 – 8–1]	113 data points, Iran	Inputs: Well head pressure (psi), choke size (1/64 in.), oil specific gravity, gas specific gravity, temperature (°F), gas liquid ratio (SCF/STB) Output: Liquid critical flow rate (STB/D)	R^2 = 0.981; RMSE = 714; ARE(%) = 2.09; AARE = 6.5
Al-Qutami et al. (2017a)	ANN (RBF)	200 data points	Inputs: Bottom-hole pressure (psi), WHP (psi), WHT (°F), Choke valve opening percentage Output: Gas flow rate (MMSCF/D)	R^2 = 0.93978; RMSE = 1.334; MAPE = 6,16
Al-Qutami et al. (2017b)	ANN 4–7 – 1 [Oil] 4–6 – 1 [gas]	591 data points	Inputs: Choke valve opening percentage (CV%), well-head pressure (psi), well-head temperature (°F), and bottom-hole pressure (psi). Output: Gas flow rate (MMSCF/D) and oil flow rate (STB/D)	Oil: R^2 = 0.965, RMSE = 1.24899; MAPE = 4.22 Gas: R^2 = 0.954; RMSE = 1.35277; MAPE = 2.27
Rostami and Ebadi (2017)	Gene expression programming (GEP) And Artificial Neural Network	119 data points South west Iran	Inputs: Choke diameter (d) (1/64 in), GOR (SCF/STB), gas specific gravity (γ), wellhead pressure (Pwh) (psi), oil API Output: Liquid flow rate (STB/D) $Q = A + B + C + D$ $A = 139.3d - 0.1GOR + 69.6\gamma - 34.8API$ $B = -21.6(d * API^{0.5}) + 34.9\gamma^2 + 0.0235(d * P_{wh}) + 492$ $C = -0.0138(\gamma * P_{wh}) * (2P_{wh}^1 - d^2 * API) * \left(\frac{\gamma + API}{d + 2GOR}\right)$ $D = 0.00548(\gamma * P_{wh}) * (\gamma + API) * \left(\frac{GOR + P_{wh} - d^2 * API}{GOR}\right)$	GEP: R^2 = 0.9342; RMSE = 383.5479; ARE (%) = 7.7492; AARE (%) = 14.8 ANN: R^2 = 0.975; RMSE = 289.535; ARE (%) = 2.139; AARE(%) = 7.915
Ghorbani et al. (2017)	Firefly optimization algorithm	92 datasets Pazanan1 gas condensate field, Aghajari Region, Iran	Inputs: Choke diameter (D_{64})(1/64 in), gas specific gravity (γ_g), flowing fluid temperature (T) (°F), upstream (P_{up}) and downstream pressure (P_{down}) (psi) Output: Gas flow rate (MMSCF/D) $q_g =$ $0.0001D_{64}^{2.3481935}\left(\frac{P_{up}}{14.7}\right)\sqrt{\left(\frac{1}{\gamma_g T}\right)0.0001\left[\left(\frac{P_{down}}{P_{up}}\right)^{1.0360972} - \left(\frac{P_{down}}{P_{up}}\right)^{1.498291}\right]}$	R^2 = 0.9677; RMSE = 0.0071; ARE (%) = 5.32005; AARE (%) = 20.21
Buhulaigah et al. (2017)	Artificial Neural Network	174 data points, Middle east	Inputs: Flowing wellhead pressure (psi), effective length (Le), ft., open hole size (inches), choke size (%), reservoir pressure (psi), average permeability (in mD), number of laterals Output: Oil flow rate (STB/D)	R^2 = 0.914
Loh et al. (2018)	Deep LSTM network model in the EnKF framework	2 mature gas wells in the North sea	Inputs: Tubing head pressure sensor 1, Tubing head pressure sensor 2, Tubing head pressure sensor 3, temperature and top-side choke valve opening, flow rate Output: Gas flow rates (MMSCF/D)	Not reported
Al-Qutami et al. (2018)	Neural network ensemble and adaptive simulated annealing	238 data points	Inputs: Downhole pressure (psi), wellhead temperature (°F), wellhead pressure (°F), and choke valve opening percentage Output: Liquid (STB/D) and gas flow rates (MMSCF/D)	ANN: RMSE = 0.0585; STDEV = 0.0046; MAPE = 4.7 Adaptive

(*continued on next page*)

Table 7 (*continued*)

Authors	Method/ Architecture	Data size/source	Inputs and Output Parameters	Performance metrics
				simulated annealing: RMSE = 0.0442; STDEV = 0.0036; MAPE = 2.35
Andrianov (2018)	Long Short-Term Memory model and ANN [2-10-10-10-1]	7855 data points	Inputs: Pressure (psi), temperature (°F) Output: Gas, oil and water flow rates	Not reported
Ghorbani et al. (2018)	MLP, RBF, LSSVM ANFIS, GEP	1037 data points from Cheshmeh Khosh, Iran	Inputs: Pressure (psi), temperature (°F), viscosity (μ), square root of differential pressure (ΔP^0.5), and oil specific gravity (SG). Output: Liquid critical flow rate (STB/D)	MLP: R^2 = 0.999998; RMSE = 54.1785; AARE = 0.128 RBF: R^2 = 0.998918; RMSE = 1291.7; AARE = 2.677 LSSVM: R^2 = 0.9982; RMSE = 1692.837; AARE = 4.2 ANFIS: R^2 = 0.999566; RMSE = 824; AARE = 2.524 GEP: R^2 = 0.999935; RMSE = 394.8156; AARE = 1.22
Mohammadmoradi et al. (2018)	Multivariate linear regression and ANN [3-8-1] (Hybrid model)	1600 data points from 12 deviated wells, Persian Gulf	Inputs: (i) Choke size (1/64 in.), wellhead pressure (psi), gas condensate ratio (SCF/STB) (ii) Choke size (1/64 in.), wellhead pressure (psi), wellhead temperature (°F) Output: Gas flow rate (MMSCF/D), Gas condensate rate	ARE (%) = (i) 1.89, (ii) 1.88 [gas] 1.89, 1.71 [for gas condensate]-MLP AARE (%) = (i) 1.09, (ii) 0.45 [gas] 0.35, 0.51 [for gas condensate]-ANN
Sun et al. (2018)	Recursive Neural Network-Long short term memory (RNN-LSTM)	Eagle Ford shale play in West Texas	Inputs: Daily oil, gas and water production data with the tubing head pressure and wellhead pressure Output: Gas, oil and water flow rates	RMSE: 81.65 RMSE: 151.27
Omrani et al. (2018)	Artificial Neural Network i. MLP, ii. LSTM	Gas well in the North Sea	Inputs for gas flow rate: Flowline Pressure (psi), wellhead pressure (psi), wellhead temperature (°F) Inputs for liquid flow rate: Bottomhole pressure (psi), wellhead pressure (psi), gas flow rate Output: Gas rate (MMSCF/D) & Liquid rate (STB/D)	MLP: R^2 = 0.98 LSTM: R^2 = 0.98
Rashid et al. (2019)	RBF-ANN-GA	276 data points	Inputs: Upstream pressure (Pup), Gas-Liquid ratio (GLR), and Choke diameter Output: Liquid critical rate	R^2 = 0.9864; RMSE = 292.3785; AARE = 2.6103
Ghorbani et al. (2019)	Genetic algorithm (GA)	182 data points Reshadat oil field, Iran	Inputs: Wellhead pressure (Pwh) (psi), choke size (D_{64}), (1/64 in); gas-liquid ratio (GLR) (SCF/STB), and basic sediments and water (BS&W) (%) Output: Oil critical flow rate $Q_L = \frac{P_{wh}(D_{64})^{1.7056}(1-BS\&W\%)^{-0.164}}{1.3522(GLR)^{0.74042}}$	R^2 = 0.997; RMSE = 562.5; ARE = −2.89; AARE = 7.33
Kalam et al. (2019)	ANN [5–19 – 1] Functional Networks ANFIS	17097 data points from 7 wells	Inputs: Flowing well-head pressure (psi), upstream temperature (°F), choke size (1/64 in.), and flowrate of condensate and water Output: Gas flow rate (MMSCF/D)	ANN: R^2 = 0.9532; AARE = 7.386 Functional network: R^2 = 0.91; AARE = 12 ANFIS: R^2 = 0.95; AARE = 14
Amaechi et al. (2019)	ANN [9–1 – 1] and Generalized Linear Model (GLM)	Production data from 224 wells, China	Inputs: Reservoir thickness (ft), shale content, porosity, permeability of the formation (mD), gas saturation, volume of fracture fluid, pump rate, fracture pressure of the formation, fluid flow-back rate Output: Gas flow rate(MMSCF/D)	ANN: MSE = 1.24 GLM: MSE = 1.57
Al Kadem et al. (2019)	ANN [3–10 – 1]	1854 data points	Inputs: Flowing wellhead pressure (psi), and choke size (1/64 in), and gas oil ratio (SCF/STB) Output: Oil flow rate (STB/D)	R^2 = 0.8; AARE = 3.7

(*continued on next page*)

Table 7 (*continued*)

Authors	Method/ Architecture	Data size/source	Inputs and Output Parameters	Performance metrics
Abedelrigeeb et al. (2019)	ANN-PSO hybrid [4–25 – 1–1] Fuzzy Logic	2445 (volatile),766 (black oil), Middle East	Inputs: Oil flow rate (STB/D), Upstream tubing pressure (psi), mixture density, Gas oil ratio (SCF/STB) Output: Choke size (1/64 in.)	ANN-PSO: R^2 = 0.913; RMSE = 15; AARE = 10.96 Fuzzy logic: R^2 = 0.89; RMSE = 18.02; AARE = 12.57
Hassan et al. (2019)	ANN [3–20 – 1] Fuzzy Logic Radial Basis Network	250 data sets	Inputs: Permeability ratio (Kh/Kv), Flowing bottomhole pressure (psi) and Lateral length (ft) Output: Liquid flow rate (STB/D)	ANN: R^2 = 0.98; AARE = 7.23 Fuzzy logic: R^2 = 0.99; AARE = 13.92 RBN: R^2 = 0.99; AARE = 11.14
Khan et al. (2019)	ANFIS SVM ANN [5–6 – 1]	1500 data points	Inputs: Choke size (1/64 in.), Upstream pressure (psi), Upstream and Downstream Temperature (°F), Oil API Gravity Output: Oil flow rate (STB/D)	ANFIS: R^2 = 0.991; AARE = 2.4 SVM: R^2 = 0.96; AARE = 3.7 ANN: R^2 = 0.994; AARE = 2.5
Nazari and Alshafloot (2019)	Extra Tree Regression Random Forest Regression & K-Nearest Neighbor Regression	4323 data points from oil fields in the Middle East	Inputs: Upstream pressure (psi), gas liquid ratio (SCF/STB), choke size (1/64 in.), temperature (°F), differential pressure (psi) water-cut (%), gas oil ratio (SCF/STB), and flow regime (critical or subcritical) Output: Gross liquid flow rate (STB/D)	Extra Tree Regression: R^2 = 0.54 Random Forest Regression: R^2 = 0.50 K-Nearest Neighbor: R^2 = 0.44
Khamis et al. (2020)	ANN Fuzzy logic SVM and Functional networks	10, 440 data points from fields in the Middle East	Inputs: Choke sizes (1/64 in.), downstream and upstream wellhead tubing pressures (psi), gas relative density, mixture density and oil API Output: Oil (STB/D) and gas flow rates (MMSCF/D)	ANN: R^2 = 0.84 Fuzzy logic: R^2 = 0.81 SVM: R^2 = 0.997 Functional networks: R^2 = 0.81
Khan et al. (2020)	ANN, ANFIS SVM Functional networks	1400 data points from an Asian oil field	Input: Choke size (1/64 in.), Upstream pressure (MPa), upstream and downstream temperatures (°F), and oil API gravity Output: Oil flow rate (STB/D)	ANN: R^2 = 0.9936; AARE = 2.5618 ANFIS: R^2 = 0.9905; AARE = 2.4355 Functional networks: R^2 = 0.9614; AARE = 3.7396
Bikmukhametov and Jäschke (2020b)	MLP neural network LSTM neural network Gradient boosting	Data from a subsea field on the Norwegian Continental Shelf	Inputs: Pressure (psi) and temperature (°F) at the bottom hole of the well; Pressure and temperature upstream of the choke; Pressure and temperature downstream of the choke; Choke opening; Well tubing length (ft); Well tubing diameter (in.); Fluid composition. Output: Oil flow rate (STB/D) & Gas flow rate (MMSCF/D)	Oil rate: MLP: RMSE = 0.0458; LSTM: RMSE = 0.0476 Gradient boosting: RMSE = 0.0463 Gas rate: MLP: RMSE = 0.0328; LSTM: RMSE = 0.278 Gradient boosting: RMSE = 0.0367
Hotvedt et al. (2020)	Hybrid model	Edvard Grieg oilfield, Norway	Inputs: Pressures (psi), temperatures (°F) and choke opening (1/64 in.), mass fraction of oil, mass fraction of gas Output: Oil flow rate (STB/D)	RMSE = 15; MAE = 8
Dutta and Kumar (2020)	ANN-FPA	20 data points from experiments	Inputs: Different sensor output voltages, pipe diameter (in.) and liquid conductivity Output: Liquid flow rate (STB/D)	RMSE = 0.75%; ARE = 99.25%
Marfo and Kporxah (2020)	Artificial Neural Network [4–2 – 1]	1600 data sets, Jubilee field, Ghana	Inputs: Gas production rate (Qg)(MMSCF/D), tubing head pressure (THP)(psi), flowing bottom-hole pressure (FBHP)(psi), production time (t) Output: Oil flow rate (STB/D) $Q_O = 766.65 - 0.32t + 738.82Q_g - 0.67THP + 0.33FBHP$	R = 0.9966; MAPE = 3.18

(continued on next page)

Table 7 (*continued*)

Authors	Method/ Architecture	Data size/source	Inputs and Output Parameters	Performance metrics
Hassan et al. (2020)	Artificial Neural Network i. [4–4 – 1] ii. [5–20 – 1]	850 data points	(i) Inputs for hydraulically fractured horizontal well: dimensionless pressure (PD), number of fractures (n), fracture conductivity (CFD), permeability ratio (Kv/Kh) (ii) Inputs for fishbone well: lateral length, number of laterals, distance between laterals, permeability ratio, flowing bottomhole pressure Output: Oil flow rate (STB/D)	i. R = 0.993; AAPE = 8.39% ii. R = 0.995; AAPE = 6.36%
Al-Rumah et al. (2020)	ANN [3–39 – 23 - 1] LSSVM SIMPLEX	1111 data points obtained from literature	Inputs: Wellhead pressure (psi), choke diameter (1/64 in.), gas liquid ratio (SCF/STB) Output: Liquid flow rate (STB/D)	ANN: R^2 = 0.9292; RMSE = 863.98; AARE = 22.06% LSSVM: R^2 = 0.9477; RMSE = 719.6; AARE = 21.5% SIMPLEX: R^2 = 0.885; RMSE = 1067; AARE = 26.8%

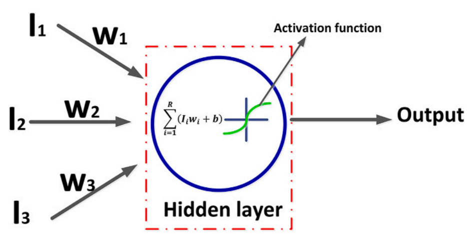


Fig. 2. Schematic diagram of an artificial neural network process.

intelligence, a seamless merger of two or more machine learning techniques with the aim of complementing each other is called hybrid computational intelligence or hybrid intelligent systems (Anifowose, 2011). The main drive for combining two techniques is due to the fact that no single technique is adequate for all predictive or classification situations (Helmy and Anifowose, 2010). The essence of combining two or more techniques is to produce a versatile and robust technique whose performance is enhanced (Tsakonas and Dounias, 2002). Hybrid intelligent systems combine the strength (or best properties) of each method while repressing the deficiencies of each individual technique in the hybrid (Anifowose et al., 2017). Hybrid intelligent systems can be built in different ways and for different reasons namely: for feature selection, architecture integration/optimization and data manipulation (Anifowose et al., 2017). Examples of hybrid techniques that are based on model parameters optimization include: Artificial Neural Network – Particle Swarm Optimization (ANN-PSO), Genetic Algorithm - Adaptive Neuro-Fuzzy Inference System (GANFIS) Artificial Neural Network – Genetic Algorithm (ANN-GA), Artificial Neural Network-Imperialist Competitive Algorithm (ANN-ICA), Particle Swarm Optimization-Least Square Support Vector Machine (PSO-LSSVM), Artificial Neural Network – Flower Pollination Algorithm (ANN-FPA), Artificial Neural Network – Teaching Learning Based Optimization (ANN-TLBO). For architectural integration, Adaptive Neuro-Fuzzy Inference System (ANFIS) can be used. For data manipulation, hybrid algorithms such as: Principal Component Analysis – Artificial Neural Network (PCA – ANN), Fuzzy Ranking – Support Vector Machines (FR-SVM), Singular Value Decomposition – Extreme Learning Machine (SVD-ELM) are used.

3.4.1.4. Support vector machine (SVM). Support vector machine (SVM) is a machine learning technique that was developed by Vapnik (1995). This technique is based on the statistic learning theory. There are basically two ideas on which the SVM technique is based. The first is margin maximisation and the second is non-linear classification. SVM is based on the concept of decision planes that define decision boundaries. An SVM model attempts to pick up the input data characteristics in order to classify and predict new observations based on the training data.

The working principle of SVM is that it finds an suitable line of separation called a '*hyperplane*' to precisely categorize two or more non-identical classes in a given classification problem. SVM uses a linear model to implement nonlinear class boundaries via some nonlinear mapping input vectors into a high-dimensional feature space (Samanta et al., 2003). The main goal of SVM is to find out the optimal hyperplane or the maximum margin classifier which is the farthest from the observations. The notation used to define a hyperplane is given by: $f(x) = \beta_0 + \beta^T x$ where β represents the weight vector and β_0 is the bias. The optimal hyperplane can be represented in an infinite number of different ways by scaling of β and β_0. A good separation of classes is achieved by having a hyperplane that has the largest distance to the nearest training data points. Generally, the training examples that are in close proximity to the hyperplane are referred to as support *vectors*. To handle non-linear data in SVM, mathematical functions called kernel functions are used. The kernel has the function of transforming input data to the required form. Examples of kernel functions include: linear, non-linear, polynomial, radial basis and sigmoid functions.

3.5.1.5. Genetic algorithms (GA). Genetic algorithm (GA) is essentially a search optimization algorithm that is rooted in the principles of natural selection. GA mirrors the idea of "*survival of the fittest*" which is a process in a natural system where the strong adapts while the weak perishes (Goodman, 2009). GA is a population based method in which the members of the population are rated on the basis of their fitness. This population represent possible solutions to the problem. The fitness value portrays a chromosome's ability to adapt and produce new offspring. Put differently, GA generates an initial population of possible solutions and then recombines them in a manner to steers their search toward more favourable areas of the search domain (Mitchell, 1995).

Basically, a GA is made up of five major processes namely: (i) a random number generation process, (ii) a fitness evaluation unit, (iii) a reproduction process, (iv) a crossover (recombination) process, and (v) a mutation operation. Whereas the reproductive process chooses the fittest candidates out of the population, the crossover process helps in the combination of the fittest chromosomes and the passage of outstanding genes to the next generation. The mutation operation helps in gene alteration in a chromosome (Bhattacharjya, 2012; Uzel and Koc, 2012). The algorithm terminates when an optimal solution (best fitness) is obtained or the maximum number of generations has been reached. Genetic Programming (GP) is the generalized form that emanates from GA (Cheng, 2007). GP is a predictive algorithm that mirrors the evolution of living organisms (Koza, 1992). Though GP and GA have the same framework, GP is a structure optimization method while GA is a parameter optimization method (Alavi et al., 2011). Another modified form of GA and GP proposed by Ferreira (2001) is the gene expression programming (GEP). The GEP algorithm generates a population of randomly chosen individual chromosomes and thereafter transforms each individual into different shapes and sizes of expression trees. These expression trees represent solutions with mathematical expressions. The GEP model has a striking similarity to the GP in that they both have the fitness function, function and terminal sets, control parameters and terminal conditions in common. (Aslam et al., 2020).

3.3.2. Parameter ranges used in AI models for oil and gas flow rate prediction

Table 8 presents a summary of the range of the parameters used in the modelling of fluid flowrate. It is evident that the important parameters are: (1) wellhead pressures, (2) GOR, (3) oil and gas specific gravity (4) choke size, (5) gas oil ratio, (6) wellhead temperature while flowrate was the output parameter. Wherever information is not indicated, it means that no actual reporting was made in the relevant reference.

From an inspection of the list, it is evident that there is no consensus on the input parameters required for modeling fluid flowrate. While most studies considered four input parameters (wellhead pressure, choke size, temperature and GOR), others included parameters such as water cut and gas liquid ratio. The widest range for temperature was in the study by Khan et al. (2019) and Khan et al.(2020) wherein temperatures are in the range of have 62–292 °F, whereas, the least range was 60–120 °F as given by Gorjaei et al. (2015). For wellhead pressure range [115–4308 psia], the highest was by Baghban et al. (2016) while the least [5.469–28.4 psia] was by Kaydani et al. (2014). For choke size range, the highest [7.7–192 (1/64 inch)] was that given by Al Kadem et al. (2019), while the least [20–37 (1/64 inch)] was given by Abedelrigeeb et al. (2019). It is observed that water cut was the least used parameter amongst the researchers, while wellhead pressure, choke size, GOR and wellhead temperature were the most used parameters.

3.3.3. Findings on AI modelling of oil and gas flow rate

Table 9 presents a summary of the major findings by various researchers on the artificial intelligence based models they developed for predicting oil and gas flow rates as showcased in Table 7. Their findings are generally situated within one or more of the following domains. The domains are accuracy of the models, performance comparison, ease of use and the application range.

In summary, from Table 9, many computational intelligence algorithms, such as artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM), and support

Table 8
Summary of range of data used by researchers on the use of AI techniques in modelling flow rate of oil and gas.

Author(s), Year	Flow rate (STB/D)	Wellhead pressure (psia)	Oil specific gravity	Gas specific gravity	GOR (SCF/STB)	**Wellhead Temperature (°F)**	Choke size (1/64 inch)	Water cut (%)	**GLR (SCF/STB)**
Al-Shammari (2011)	639–21300	92–1550	25.4–47.5		11–6300	160–233		0–97.5	
Al-Khalifa and Al-Marhoun (2013)	268–26400	38–3141	0.765–0.997	0.708–1.4	10–5812	141–326	12–172	Not available	Not available
Kaydani et al. (2014)	100–4500	5.469–28.4			400–1500	120–180	0.2m–3.2 m		
Elhaj et al. (2015)	2.17–17.17 MMScf/d	520–1840		0.588–0.632		535.2–564	16–128		
Seidi and Sayahi (2015)	11.3–113 MMscf/d	14.5–1407				109–211	40–192	Not applicable	0.688–32.215
AlAjmi et al. (2015)	692–8028	830–1590	Not available	Not available	224–4574	69–147	16–73	0–64.5	97.3–4574
Baghban et al. (2016)	198–9646	115–4308			158–20324		16–112		
Buhulaigah et al. (2017)	972–9350	276.8–1621					5–100		
Gorjaei et al. (2015)	668.4–14480.8	1646–3000					21–68		828.1–13095.1
Al-Qutami et al. (2017b)	4712.9–14190	3843.8065 - 4642.658				143.06–149.9	10.9–34.3		
Rostami and Ebadi (2017)	198–9643	115–4308	22.97–43	0.63–1.04	158–20324		16–112		
Choubineh et al. (2017)	1324–22150	50–2940	0.808–0.92	0.6886–1.236	107–3660	90–135	24–80	Not available	Not available
Ghorbani et al. (2017)	0.27–55.590	284–6115		0.62–0.82		80–163	16–80		
Ghorbani et al. (2018)	2195–119005	0.8–250	0.8820–0.997			57.2–240.8			
Kalam et al. (2019)	1.82–87.71 MMSCF/D	47.62–1590			174–1981		4–100		
Ghorbani et al. (2019)	205–34450	133–881					25.6–64		36–885
Abedelrigeeb et al. (2019)	735–25396	280–1600	32–37		14–3200		20–37		
Khan et al. (2019)	211–1795	241–1483	26.9–31			62–292	12–54		
Al Kadem et al. (2019)	1073–19526	222–1589					7.7–192		
Khamis et al. (2020)	312–20308	200–1360			100–3507		17–159		
Khan et al. (2020)	210–1795	240–1483	26.9–31			62–292	12–54		

vector regression (SVR), were reported as effective for estimating oil and gas flow rates. One point that runs through the findings of the researchers is that the AI models have good predictive capability, however, they agree that the performance of these machine learning models could be improved through hybridization with other machine learning methods especially evolutionary algorithms. Such hybrids provided more robust and efficient models that can effectively learn complex flow systems in 3.3.4an adaptive manner. Although literature includes numerous evaluation performance analyses of individual machine learning models, there was no definite conclusion reported with regards to which models function better in certain applications.

3.3.4. *Critique of the artificial intelligence (AI) based models reported in literature*

This section of the paper takes a critical look at the AI models for predicting oil and gas flow rate as extracted from the literature. The critique looks at the applicability of the model in the field, its replicability, its generalizability and the computational cost of the models. In order to be objective, this critique restrained itself from implicitly assigning more weight or credence to one study over another based on any criteria, rather its focus is twofold: (i) To critically explore the strengths, weaknesses and scope of each of these models and how the challenges and gaps in each model is helping to shape the trend in the evolving improvement of fluid flow rate models (ii) To serve as a form of feedback that would help further/deepen knowledge on the subject.

3.3.4.1. Input feature selection and field applicability of the models. One major problem with most AI solutions published so far is in the choice of the input variables. Selecting the most relevant input features for training and testing is fundamental to simplifying the models and enhancing their performances. This problem explains some of the challenges of field applicability of the models. It is important to mention

Table 9
Summary of findings by researchers on the use of AI techniques in modelling critical flow rate of oil well fluids.

Author(s), Year	Method used	Major findings and conclusions
ZareNezhad and Aminian (2011)	Artificial Neural Network	The model can be utilized for a robust design of wellhead chokes under subcritical flow conditions of gas condensates.
Berneti and Shahbazian, (2011)	ANN and Imperialist Competitive Algorithm (ANN-ICA)	The predictive performance of the ICA-ANN soft sensor outweighs that of ANN; because ICA-ANN combines both the local and global searching ability of the ANN and ICA respectively.
Ahmadi et al. (2013)	ANN, Fuzzy Logic, Artificial neural network - Imperialist Competitive Algorithm (ANN-ICA)	Of the three methods used in the work, the ANN-ICA technique performed better than the fuzzy logic and artificial neural network techniques.
Seidi and Sayahi (2015)	Genetic algorithm	The proposed model is capable of estimating high flow rates of gas condensate wells under sub-critical conditions particularly in case of large choke sizes.
Elhaj et al. (2015)	ANN, Fuzzy logic SVM, Functional network, Decision tree	Of the five techniques studied, the fuzzy logic and artificial neural network techniques gave the best results for gas flow rate prediction.
Hasanvand and Berneti (2015)	Artificial Neural Network	The ANN multiphase flow meter eliminates the need for a separator and has no source of radioactive emissions, thus is safe for both field personnel and the environment.
Zareiforoush et al. (2015)	Artificial Neural Network	The proposed ANN model can predict wet factor with 95% accuracy.
Choubineh et al. (2017)	Hybrid method (ANN-TLBO)	(i) Beyond being useful for prediction of liquid critical flow rate in oil wells in Southern Iran, it could as well be used worldwide (ii) A modest increase in prediction capability was observed with the six parameter models compared to the three parameter model.
Rostami and Ebadi (2017)	Gene Expression Programming (GEP) Artificial Neural Network	The ANN model performed better than the GEP model. However, ANN does not establish an explicit mathematical relationship between the input and output parameters whereas the GEP model can present explicit correlations which can be integrated easily into commercial software
Buhulaigah et al. (2017)	Artificial Neural Network	In comparison with other models, the neural network model proved to be more accurate given the dataset used.
Ghorbani et al. (2018)	MLP, RBF, LSSVM ANFIS and GEP	The predictive accuracy was highest for the MLP algorithm while the GEP and RBF also achieved high levels of accuracy. However, the ANFIS and LSSVM algorithms performed less, especially in terms of predicting low flowrates in the region of $<$40,000 STB/day.
Andrianov (2018)	LSTM and ANN	The LSTM model performed better than the ANN model even when a single pressure reading is used for the training.
Al-Qutami et al. (2018)	Neural network ensemble and adaptive simulated annealing	The proposed model performs well in its predictions and is inexpensive to develop compared to existing models. Though ensemble techniques may attract additional computational costs, this is offset by the enhanced performance achieved
Kalam et al. (2019)	ANN, Functional Networks and ANFIS	The ANN model had higher prediction accuracy than the FN and ANFIS models with accuracy levels in excess of 90% being recorded
Abedelrigeeb et al. (2019)	ANN-PSO	The predictive capability (in terms of speed and accuracy) of the hybrid of ANN and PSO was higher than that of the fuzzy logic model
Hassan et al. (2019)	ANN, Fuzzy Logic Radial Basis Function	In forecasting the productivity of the fishbone wells, the neural network model outperformed the fuzzy logic and the radial basis function models
Amaechi et al. (2019)	ANN and Generalized Linear Model (GLM)	From the analysis, it was observed that the ANN model performed better than the GLM model with both models having a mean square error of 1.24 and 1.57 respectively.
Rashid et al. (2019)	Artificial Neural Network	The proposed model is valid given the how close the errors of the training, testing and validation datasets are to each other.
Khan et al. (2019)	ANFIS, SVM, ANN	In comparison with other correlations developed in the work (ANFIS, SVM) and those existing in literature, the ANN performed better than these correlations.
Khamis et al. (2020)	ANN, Fuzzy Logic SVM, Functional Networks	Comparing the four techniques of ANN, fuzzy logic (FL), SVM and functional networks in terms of their predictive capability, the fuzzy logic model gave the best predictions.
Khan et al. (2020)	ANN, ANFIS SVM, Functional networks	Among the four techniques of ANN, ANFIS, SVM and functional networks utilized, the ANN technique proved to provide the optimal model.
Dutta and Kumar (2020)	Artificial Neural Network – Flower Pollination Algorithm (ANN-FPA)	Owing to the few number of parameters to be adjusted during the process of optimization, the ANN and flower pollination can easily be implemented. The proposed ANN-based FPA method has the capability to solve problems in real time with great precision.
Marfo and Kporxah (2020)	ANN and Decline Curve Analysis methods	In comparison with the decline curve analysis methods (Exponential, Harmonic and Hyperbolic), the ANN model has a better predictive capability with higher accuracy
Hassan et al. (2020)	Artificial Neural Network	The proposed ANN model has the ability to compute well performance in a relatively simple manner and can easily be incorporated into commercial software.

that a greater percentage of the AI based models developed presently make use of gas oil ratio (GOR) or gas liquid ratio (GLR) as input. First, Elgibaly and Nashawi (1998) asserted that the total GOR is usually not obtained from routine production tests but are determined from PVT analysis. Al-Qutami et al. (2018) shared the same viewpoint when they reported that GOR is usually obtained from laboratory sampling and therefore cannot be used to determine flow rate in the field.

Second, in most oil field operations, the produced gas is either vented or flared and as a result the value of the stock-tank GOR is usually not available (El-Banbi et al., 2018). To estimate stock tank GOR, models dependent on conditions at the primary separator are utilized. This fact resonates with the view held by Zhou et al. (2018) wherein they reported that in most field conditions, accurate measurements of the input data, such as pressure, temperature, and GOR have large uncertainties. Mohammadmoradi et al. (2018) zooms in on this same point. They opined that during the field production lifetime, there are influential variables that are not exactly known or continuously monitored one of which is the condensate gas ratio.

Third, a close look at the in-house company models as shown in Table 12 used by companies indicate that the GOR/GLR parameter is conspicuously missing, thus suggesting that it may not be relevant for field computation of fluid flow rates. Bokhamseen et al. (2015) also found out through sensitivity analysis that condensate gas ratio (CGR) had an insignificant effect on gas flow rate prediction. According to Woodroof (2020), the total gas oil ratio is typically not fully measured in a well test; hence, the gas flow rates of a multiphase flowmeter (MPFM) cannot be reliably validated. Furthermore, the fact that engineers prefer to use easily obtained parameters in any engineering calculation (Leal et al., 2013) makes the use of the models that include GOR in their models irrelevant for field application.

In summary, since GOR when used as an input cannot be measured by relatively inexpensive means due to its variation with composition, thus, utilizing it as an input would not quite be economical. Nonetheless, several studies adopted this parameter for predicting oil and gas flow rate. However, it must be stated that not all the studies reviewed made use of this parameter. Cases where this parameter was excluded or not taken into consideration are in the works of Elhaj et al. (2015), Al-Qutami et al. (2018), Khan et al. (2019), Khan et al. (2020), Bikmukhametov and Jäschke (2020b). While GOR is a sticky point to handle, other researchers have zoomed in other factors such as temperature and water cut. For instance, Zhou et al. (2018) reported that while choke size and upstream pressure are the two most important parameters affecting prediction performance, however by contrast, the effects of water-cut and temperature are relatively small. In addition, some researchers developed models to determine the flow rate wherein they used parameters that are difficult to obtain in real time; an example of such parameter is reservoir permeability as seen in the works by Hassan et al. (2019) and Buhulaigah et al. (2017) as well as fluid properties such as fluid viscosity as seen in the work by Ghorbani et al. (2018). Finally, the lack of sensitivity analysis on the impact of the input variables on oil and gas flow rate prediction for most of the studies reported is considered missing points in the literature.

3.3.4.2. (ii) replicability of model results. Replicability is the foundation that enables the independent validation of the findings or results of a research (Dou et al., 2018). According to Miłkowski et al. (2018), the ability to reproduce/replicate the results of a scientific model is closely linked with some of the general features of a scientific study. The possibility to replicate the results from published research is one of the major challenges in model development using AI. This makes it somewhat challenging to re-implement AI models based on the information in the published research. The reason being that the details of the model have not been made available. For instance, AI techniques such as ANN used by most researchers in the literature for developing flow rate correlations have been inadequate because the necessary details of the model namely the weights and biases of the network that can be used for reproducing the results of the models were not presented by the researchers. Instances are found in the works of Al-Khalifa *et al.* (2013); Ahmadi et al. (2013); Zangl et al. (2014); Okon and Appah (2016); Buhulaigah et al. (2017); Rostami and Ebadi (2017); Amaechi et al. (2019); Marfo and Kporxah (2020); Khamis et al. (2020); Bikmukhametov and Jäschke (2020b). However, only a few included these details in their work. They are Hassan et al. (2019), Hassan et al. (2020), Khan et al. (2019) and Khan et al.*(*2020).

To underscore the importance of these details, Chaabene et al. (2020) states that an explicit vector of weights and biases coupled with a fixed number of hidden layers and hidden neurons obtained after numerous trials results in a well-defined ANN model. Secondly, an impediment to the use of most AI techniques such as support vector machine (SVM) and ANN is their black box nature which do not allow for a clear mathematical equation relating the input data to the output; thus, they are not user-friendly and cannot be integrated into commercial software. Little wonder, Bikmukhametov and Jäschke (2020b) opined that AI models are often considered as black-box solution which is one reason they are still not widely used in operation of process engineering systems. However, one AI technique – the gene expression programming (GEP) or multigene genetic programming (MGGP) is one that can evolve explicit equations which could easily be integrated into commercial software (Rostami et al., 2017). These explicit models can be seen in the works by Rostami and Ebadi (2017); Kaydani et al. (2014) and Ghorbani et al. (2017) and Ghorbani et al. (2019).

3.3.4.3. Generalizability of the models. The functionality and robustness of a model resides in its ability to generalize. Generalization simply put refers to the consistency in which a model predicts when unseen data is supplied to it (Kronberger, 2010). According to Alexander et al. (2015), the gold standard for gauging a model's generalizability is to subject it to an independent dataset (data that was not used to develop the model). Using an independent dataset is vital as it reveals the true predictive capability of the model (Lawson and Marion, 2008).

According to Beck and Kurz (2020), generalizability of a model is one of the most prized features of any model. They added that generalizability of a model is not just limited to the model's applicability beyond its training regime, but also includes a reliable backup structure in cases where the model has the potential to fail. While ANN is the preponderant method used by most researchers to develop oil and gas flow rate models, it must be said that it has a strong ability to find the local optimistic solution while it weak in finding the global optimistic solution. Hence, this most likely has a great effect on the generalizability and robustness of the models developed especially for models that were not cross validated. As a solution to the local convergence problem, Christou et al. (2019), asserts that using Extreme Learning Machines (ELM) as an alternative method can put the problem to rest.

3.3.4.4. Complexity and computational burden of developed models. According to Beck and Kurz (2020), it is generally observed that a model would gain wider acceptability amongst a community of users if the model is computationally cheap, robust and easy to understand and implement. Hence, a balance has to be struck between a model's complexity or completeness, its prediction time and its accuracy or precision (Downton, 2012). Most of the models reviewed in this work were developed using ANN. According to Bonfitto et al. (2019), the network architecture chosen by the user determines how effective and accurate an ANN model would be. This is because the chosen architecture may cause the resulting network to occupy much space in the program memory while also increasing the processing time (Bonfitto et al., 2019). Memory occupation is directly linked to the number of neurons contained in the hidden layer of the network.

Though several ANN architectures have been proposed by diverse authors in the literature for predicting oil and gas flow rates, however, to the best of the authors' knowledge, there is no mention of the computational burden of these architectures by any of them; hence the computational cost of the ANNs are missing points in the literature. Thus, for a given model, a compromise has to be made between the model's effectiveness and its memory consumption. This work therefore aligns itself with the thoughts of Kalechofsky (2016) who posits that having a complex model is not consistent with having good predictions.

3.3.4.5. Model performance assessment. There is need for quantifying the performance of a model after it has been trained and subjected to a test data (Scheinost et al., 2019). The performance of a model essentially entails computing the deviations between the actual values and the model's prediction. This can be evaluated in diverse ways. Thus, defining the chosen metric before the analysis is necessary (Scheinost et al., 2019).While there exist so many metrics that can be used to assess the performance of models, some of the studies reviewed used only a single statistical metric to assess the performance of their model. This is found in the works by Baghban et al. (2016) and Nazari and Alshafloot (2019) wherein they used only the goodness of fit (R^2) while Amaechi et al. (2019) and Bikmukhametov and Jäschke (2020b) used the MSE and RMSE values to assess their models performance respectively. Bello et al. (2014) mentioned that they used the absolute error metric, however, the values were missing. Others utilized two metrics as follows: Dutta and Kumar (2020) – (RMSE and accuracy); Zangl et al. (2014) – (R^2 and average error metrics); Marfo and Kporxah (2020) and Hassan et al. (2020) – (the correlation coefficient (R) and mean absolute percentage error); Ahmadi et al. (2013) – (R^2 and MSE); Beiranvand and Khorzoughi (2012) – (average error and average absolute error) while ZareNezhad and Aminian (2011) made use of three statistical metrics. It is interesting however to mention that Rostami and Ebadi (2017) made use of 11 metrics to evaluate the performance of their models. Concerns raised about the performance of some metrics such as RMSE and MAPE by Al-Qutami et al. (2018) indicate that though both metrics can be used to assess a model's performance, however, they do not show how accurate the model is for the flow metering application. Hence, they recommended the use of the cumulative deviation plot.

Criticisms have trailed the use of some of these metrics especially when used as the only means of assessing a model's performance. For instance, Spiess and Neumeyer (2010) asserts that using R^2 as the only means of demonstrating the validity of a model is not state-of-the-art. In its place, they suggested that either the Akaike Information Criterion or the Bayesian Information Criterion value should be used. Archontoulis and Miguez (2015) also zooms in on this same point. They posit that although often used, the R^2 does not represent a good metric of model performance for nonlinear models. Li (2017) also shares the same sentiments. He argues that R and R^2 beyond being incorrect, does not measure a model's accuracy except if the values for the actual and predicted match perfectly. Wallach (2006) listed one of the limitations of the R^2 value as not being able to account for the number of parameters and advised that other metrics or combinations of metrics should be used. Finally, one drawback of using R^2 as a performance metric is that it can show very good results even when the output has a large variance. Hence, the R^2 value can be misinforming if there are a few output values that are far away from the overall scatter of the actual and predicted values. In this case, these few points can increase R^2 artificially (Kuhn and Johnson, 2019). In summary, while we do not claim that any one metric is better than another, rather a combination of metrics would be more useful in assessing a model's performance.

3.3.4.6. Effect of data size. According to Hemmati-Sarapardeh et al. (2020), the reliability or otherwise of AI models has a lot to do with the quality and size of the data used for developing the model. Using a large sized dataset with a wide range of data points will lead to the development of a better predictive model with the model being more likely to pick up on generalizable features (Hemmati-Sarapardeh et al., 2020). Furthermore, the use of large datasets increases the power to discern the relationships amongst input variables and the output and decreases the chances of overfitting.

As seen in Table 7, most of the extant models exhibited good performances by dealing with databases of different sizes. According to Hemmati-Sarapardeh et al. (2020), utilizing more than 100 experimental points for building the intelligent models leads to reliable results. Going by this, about 10% of the models in Table 7 were developed with less than 100 data points. This cold start problem arising due to lack of sufficient data is worth looking into. However, it is gratifying to note that 90% of the studies utilized datasets having a wide range with a good number of data points.

In addition, some studies developed ANN models using minimal number of data points and reported training coefficients close to 1. This is despite the well-known guidelines in ANN literature that the ratio of number of data points to the number of weights in the network should be greater than or equal to 2 to avoid overtraining (Kakar, 2018). Here, the weights of the network are the unknown variables and the training set is the number of equations. Thus, the sum of the all weights in a network at least must be equal to number of training set data. For instance, to develop an ANN model consisting of 3 input neurons, 12 hidden neurons and 1 output neuron, [(3x12) + (12x1)] = 48 unknown variables must be estimated by neural network; then at least 48 data points are required as the training data. This was not seen in the works of Okon and Appah (2016); Choubineh et al. (2017) and ZareNezhad and Aminian (2011). This may have led to overtraining of the network. Moreover all of the studies listed above did not discuss how they handled their model to avoid the overtraining of the network.

4. Predicting flowrate of oil and gas using a fusion of sensors and artificial intelligence techniques

Traditional sensors incorporating soft computing techniques provide an effective solution to the measurement of phase flowrates. Indirect techniques based on traditional sensors incorporating soft-computing algorithms, such as artificial neural network (ANN), support vector machine (SVM), least-squares support vector machines (LSSVM) and extreme learning machine (ELM) together with genetic algorithms or particle swarm optimization, have also been applied to two-phase or multiphase flow measurement. Some sensors that can be utilized with these AI techniques include: wire mesh sensors (WMS), ultrasonic and differential pressure sensors etc. According to Xu et al. (2020), these methods are practicable in the laboratory and not in the field. The studies where a combination of these sensors was made with AI techniques is presented in Table 10. From Table 10, it is observed that ANN was the AI technique mostly utilized for the ensemble models.

4.1. Findings on using a fusion of sensors and AI methods in modelling of oil & gas flow rate

Table 11 provides a summary of the findings by researchers who used a fusion of sensors and AI techniques for predicting oil and gas flowrates. From the summary, the ANN algorithm is the most frequently used AI method for fusion with sensors. Other techniques such as SVM and genetic programming have also been reported. In some studies where ANN and SVM were used, the researchers reported the superiority of the SVM over the ANN algorithm in terms of accuracy and robustness. While most of the studies reviewed reported remarkable results and possible field applicability for the hybrid system, the combination (Venturi tube and dual electrical capacitance tomography (ECT) sensors + convolutional neural network (CNN)) proposed by Xu et al. (2020) was said to be unsuitable for field application owing to the fact that the combined CNN and ECT had a high computational burden.

Table 10
Traditional sensor fusion with machine learning algorithms.

Reference	Sensor	AI technique	Inputs from sensor & Outputs + data size	Performance
Sheppard and Russell (1993)	Gamma-ray densitometer	ANN	Input: 12 time series measurements Output: Gas & liquid mass flow rates [12 data sets]	Root mean square: 13%
Geng *et al.* (2006)	Slotted orifice	ANN [9-7-2]	Inputs: Signal features in time and frequency, fluid properties, pipeline parameters Output: Gas and liquid mass flow rate	Relative error Gas:±6% Liquid: ±12%
Huang et al. (2009)	Conductivity sensor	LSSVM	Input: Not stated Output: Total volume flow rate and total mass flow rate of oil-water two-phase flow [104 conductivity values]	Maximum relative error of the total volume flow rate is < ±1.0%. Relative error of total mass flowrate <5%
Meribout *et al.* (2009)	1) Venturi sensor and 2) conductance, capacitance, ultrasonic, or differential pressure sensor	ANN	Inputs: ρ, venturi, and ΔP probes Outputs: Gas, oil & water flow rates [240 data points]	Average error Gas: 4.68% Oil: 6.20% Water: 3.91%
Xu et al. (2011)	Throat-extended Venturi meter (TEVM)	ANN [11-20-1] [Gas] [11-18-1] [Water] SVM	Inputs: Signals from: differential pressure (DP) across the converging section and a DP across the extended throat section, temperature, and static pressure Output: Gas and liquid flow rate [1460 data vectors] [Wet gas flow]	Relative error Gas: SVM – .86% Gas: ANN – .14% Water: SVM – 4.25% Water: ANN: 4.77%
Shaban and Tavoularis (2014)	Differential pressure sensor	ANN	Inputs: Five features from the time histories of ΔP, and the correlation coefficient of the pressure fluctuations measured by the two pressure transducers in the test section Outputs: Gas and liquid flow rate [570 data points]	Average absolute relative error (i) Liquid: 6.1–8.7 (ii) Gas: 6.2–16
Wang *et al.* (2017)	Coriolis flowmeters	BP-ANN RBF-ANN SVM GP	Inputs: Observed density drop, apparent mass flowrate, damping, and DP Outputs: Gas and liquid flow rates [237 data points for ANN]	
Bahrami *et al.* (2019)	Piezoresistance differential pressure transducers, inline viscometer & thermometer	ANN [5-7-7-3]	Inputs: Temperature, viscosity, standard deviation, coefficients of skewness and kurtosis Output: Gas, oil water flow rates [5400 sets of data from two oil fields]	R^2 value Gas: 0.997 Oil: 0.997 Water: 0.995
Jeshvaghani *et al.* (2019)	Gamma-ray attenuation	ANN [2-5-2-2]	Inputs: Detector counts and pressure difference Outputs: Air & water flow rates [32 data points]	*For air:* RMSE: 10.71; MRE: 0.86% For Water: RMSE: 2.14; MRE: 1.27%
Li *et al.* (2020)	Cone throttle device	ANN [8-12-1] [Gas] [8-17-5-1] [Liquid]	Inputs: Gas density, Three probability density function (PDF) and two power spectral density (PSD) of the upstream-throat differential pressure (DPwg) signals, Mean values of: upstream-throat DP, permanent pressure loss Outputs: Gas & Liquid flow rate [442 data points]; [Wet Gas flow]	*For gas* MAPE: 1.53 MRE: 0.05 & *For liquid* MAPE:12.83 MRE: −3.66
Dave and Manera (2020)	Wire mesh sensor (WMS)	ANN CNN FNN	Inputs: Not stated Outputs: Super ficial velocities for gas-liquid flows	Not stated
Xu *et al.* (2020)	Venturi tube and dual electrical capacitance tomography (ECT) sensors	CNN	Inputs: Flow patterns obtained by image construction Outputs: Oil flow rate, gas flow rate [520,000 data points]	Average relative error: oil flow rate is 4.6%; gas flow rate is 1.4%

5. Company based flow rate prediction models

In estimating oil and gas flow rate, each company have their unique technique or model. These models are largely based on experience or on empirical analysis. Table 12 highlights these models and the respective companies that apply them. It is observed that the models are mainly for predicting gas flow rates. For most of the models, wellhead pressure, choke size and wellhead temperatures were the predominantly used input parameters. Unlike the models for predicting gas flow rate in Table 4 that have GLR or CGR as input parameters, these company based models for predicting gas flow rate are completely devoid of this parameter. Owing to the confidentiality of the models, the models' co-efficients are not included.

6. Summary, conclusions and recommendations

This study has comprehensively and systematically identified and critically appraised papers which either developed novel correlations or updated existing prediction models for oil and gas flow rate through chokes. The work assessed their performance and highlighted errors that may have been made in their formulation. A total of 120 flow rate correlations were isolated and critically reviewed. Among them, 44 correlations are based on the non-linear regression technique, 6 are in house company based models, 9 correlations are theoretical based models, 49 correlations are based on AI techniques and 12 correlations are based on an amalgam of sensors and machine learning models. This paper avoided an encyclopaedic account of every paper on this subject; rather it made an in-depth discussion of current progress and challenges highlighting those areas of interest and significance. Based on this, the following conclusions are drawn:

- Most of the oil and gas flow rate prediction models are either limited in the range of application due to data constraints or are too regional in their application. Many of the empirical and AI based models were developed for oilfields in the Middle East region.
- It is observed that the size of the dataset used for developing the models varies from one study to another. Studies that considered fewer data examples may record accurate results. However, the models developed in these instances have the tendency to come off with higher error values when exposed to new data compared to those developed from more extensive databases.
- While it is attractive to attempt making models comprehensive by incorporating numerous input variables, the model could become so

Table 11
Summary of findings by researchers in using traditional sensors with machine learning algorithms in predicting oil and gas flow rates.

Reference	Sensor, AI technique	Major findings
Sheppard and Russell (1993)	Gamma-ray densitometer + ANN	While ANN is effective in its predictions, however, its performance can be enhanced by: (i) utilizing a dataset with a wide coverage that accommodates all flow rate combinations (ii) instead of just one network, using a series of networks to characterize flows in separate regimes while using one network as the controller.
Geng *et al.* (2006)	Slotted orifice + ANN [9–7 – 2]	Results obtained show that the method provides an efficient means for developing 2-phase flow meters. The ANN output is stable and repeatable with the technique of ANN ensemble
Meribout *et al.* (2009)	1) Venturi sensor and 2) conductance, capacitance, ultrasonic, or differential pressure sensor + ANN	The results indicate that classification in real-time for up to 90% gas fraction can be obtained with a relative error <10%
Xu et al. (2011)	Throat-extended Venturi meter (TEVM) + ANN [11-20-1] [Gas] [11-18-1] [Water] SVM	The proposed combination of AI techniques with TEVM yielded an easy but viable technique to the metering of wet gas. Both the SVM and ANN models developed were able to capture the complex relationship between the 2-phase flow rates and the signal features. In comparison, the SVM method outperformed the ANN method in the prediction of the gas and water flow rates.
Shaban and Tavoularis (2014)	Differential pressure sensor + ANN	It was observed that the (i) probability density function and (ii) power spectral density of the differential pressure signals were strong indicators of the phase flow rates. The independent component analysis was useful in preserving most of the information embedded in these two flow properties and enabled their usage without requiring an unreasonably huge amount of calibration measurements.
Wang *et al.* (2017)	Coriolis flowmeters + BP-ANN, RBF-ANN, SVM, GP	On the basis of accuracy and robustness, the SVM model outperformed the models developed using the BP-ANN, RBF-ANN and GP.
Bahrami *et al.* (2019)	Piezoresistance differential pressure transducers, inline viscometer & thermometer + ANN [5-7-7-3]	Incorporating the ANN with the pressure signals, detectors can be used without transmitter, hence a reduction in cost is achieved. This combination would use radioactive transmissions which detrimental to field personnel and the environment. The possibility of having the measurements done in different operating conditions (temperature, pressure, GOR etc.), implies it is possible to use it for many years without the need for calibration
Jeshvaghani et al. (2019)	Gamma-ray attenuation + ANN [2-5-2-2]	Using this gamma-ray attenuation + ANN model combination would enable an efficient prediction of flow rates at varying temperatures even when the proposed ANN is trained only at a specific temperature. This way, the need for either using several ANNs or the need for the recalibration of the measuring system would be eliminated.
Li *et al.* (2020)	Cone throttle device + ANN [8-12-1] [Gas] [8-17-5-1] [Liquid]	The advantages of the proposed combination (cone throttle device + ANN model) include: its high accuracy, inexpensive nature, ease of implementation. The cone has the capability to provide valid and sensitive differential pressure (DP) signals for bringing out features as pointers of the liquid and gas flow rates
Dave and Manera (2020)	Wire mesh sensor (WMS) + ANN, CNN FNN	The combination of WMS and neural network has the potential to yield accurate estimations of super ficial velocities in gas-liquid flows. It is possible to train only one neural network for the purposes of estimating the flow rate for multiple flow regimes.
Xu *et al.* (2020)	Venturi tube and dual electrical capacitance tomography (ECT) sensors + CNN	The CNN algorithm has a high computational burden; currently, it is difficult to integrate it into measurement devices in the industry, neither is it possible for them to be transformed into portable devices. Therefore, there is need to improve and reduce the computational cost of the ECT image reconstruction algorithm in order for it to be useful to the industry. Real-time flow measurement in the field is difficult using this method.

Table 12
Flow rate correlations of worldwide services/operator companies.

Company	Correlation
Schlumberger (SLB)	$Q_g = (a_1 C.S.^2 + a_2 C.S. + a_3) * WHP/(S.G. * (WHT + 460))^{\frac{a_4}{1000}}$
Halliburton	$Q_g = \frac{[(C.S./64)^{b_1} * b_2 * b_3 * (WHP + b_4)]}{(S.G. * (WHT + 460))^{b_5} * (wet\ factor/1000)}$
Eni	$Q_g = c_1 * WHP/(S.G. * (WHT + 460))^{\frac{c_2}{1000}}$
Texas A & I	$Q_g = d_1 * C_d * A * WHP/(S.G. * (WHT + 460))^{\frac{d_2}{1000}}$
Dry gas correlation	$Q_g = e_1 * (WHP + e_2) * (C.S.)^{\frac{e_3}{1000}}$
Saudi Aramco	$q_g = 0.479\left(\frac{D_{64}}{64}\right)^{2.0871} * \frac{0.7P_{up}}{\sqrt{\gamma_g T}}$ [old model]
	$q_g = 0.00149228 D_{64}^{2.118654173}\left(\frac{P_{up}}{14.7}\right)\sqrt{\left(\frac{1}{\gamma_g T}\right)1.586085251\left[\left(\frac{P_{down}}{P_{up}}\right)^{0.739034} - \left(\frac{P_{down}}{P_{up}}\right)^{1.369516866}\right]}$ (Source: Leal et al., 2013)

NB: Q_g = gas flow rate (MMSCF/D); D_{64} = C.S = C_d = choke size (1/64 in.); WHT = wellhead temperature (°F); WHP = wellhead pressure (psi); S.G. = specific gravity; P_{up} = Upstream pressure (psi); γ_g = gas specific gravity; T = temperature (°F); P_{down} = downstream pressure (psi); a_1, a_2, a_3, a_4, b_1, b_2, b_3,b_4, b_5 c_1, c_2, d_1, d_2, e_1, e_2, e_3 = constants.
(Source: Zareiforoush et al., 2015)

complex so much so that the results are no longer transparent and its field applicability becomes nearly impossible.

- In developing a model, a good balance has to be made regarding the model's computational demand, its complexity, prediction time and ease of use.

The following are the recommendations for future studies:

- Developing models which meets the needs of the user in the field (e.g. models requiring easily obtained input parameters that are readily available in their databases) is an area to be explored. This would assist such users make quick real-time decisions in the field.

- For the insights from the different models to be useful, it is necessary that models be transparent. Although there are varied views on what makes up an acceptable degree of transparency, it almost always refers to a disclosure of model's basic assumptions, algorithms, weights, biases, coefficients as well as the data used to develop the model. Including these as part of a research work is recommended.
- It is inevitable that noise would always be part of real time or dynamic data. A model that performs well in predictions with clean data could be thrown into disarray by an unexpected stream of noise in the data. To forestall this, incorporating noise to data during model training and development would make for a more robust model in the presence of noise. This is an area open for research.

Credit author statement

Okorie Agwu: Conceptualization, Methodology, Investigation, Writing-original draft. Emmanuel Emeka Okoro: Methodology, Writing - original draft, Writing-review & editing. Samuel E. Sanni: Revision, discussion, resources, improvement,

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors are grateful to the management of the University of Uyo and Covenant University for providing an enabling environment for this research.

Symbols and Nomenclature

Ac	Choke throat area
AARE	Average Absolute Relative Error
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN-FPA	Artificial Neural Network – Flower Pollination Algorithm
ANN	Artificial Neural Network
ANN-PSO	Artificial Neural Network-Particle Swarm Optimization
ANN-TLBO	Artificial Neural Network -Teaching-learning-based optimization
API	American Petroleum Institute
ARE	Average Relative Error
AARE	Average Absolute Relative Error
BHP	Bottom Hole Pressure
BS&W	Basic Sediments & Water
C_D	Discharge Coefficient
CNN	Convolutional Neural Network
C.S	Choke Size
GA-RBF	Genetic Algorithm-Radial Basis Function
GEP	Gene expression programming
GLR	Gas Liquid Ratio
GOR	Gas Oil Ratio
GVF	Gas Volume Fraction
ICA	Independent Component Analysis
LGR	Liquid Gas Ratio
LSSVM	Least-Squares Support Vector Machine
LSTM	Long Short-Term Memory
M	Total pound mass of oil, gas and water per stock tank oil
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MGGP	Multigene genetic programming
ML	Machine Learning
M_L	Mass liquid flow rate
MLP	Multi Layer Perceptron
MPFM	Multiphase flow meters
MSE	Mean Square Error
PCA	Principal Component Analysis
PDF	Probability Density Function
PSD	Power Spectral Density
PVT	Pressure Volume Temperature
Q	Flow Rate
R^2	Goodness of fit
RBF	Radial Basis Function
RNN	Recurrent Neural Networks
SVM	Support Vector Machines
VFM	Virtual Flow Metering
WHP	Well Head Pressure
WHT	Well Head Temperature

References

Aalst, W.M.P., Rubin, V., Verbeek, H.M.W., Van Dongen, B.F., Kindler, E., Günther, C.W., 2010. Process mining: a two-step approach to balance between underfitting and overfitting. Software Syst. Model 9, 87–111. Number 1.

Abdul-Majeed, G.H., 1988. Correlations developed to predict two-phase flow through wellhead chokes. June 12 - 16. In: Paper PETSOC-88-39-26 Presented at the 39th Annual Technical Meeting of the Petroleum Society of CIM Held in Calgary, pp. 1–14. https://doi.org/10.2118/88-39-26.

Abdul-Majeed, G.H., Maha, R.A., 1991. Correlations developed to predict two phase flow through wellhead chokes. J. Can. Pet. Technol. 30, 47–55.

Abedelrigeeb, A., Baarimah, S.O., Al-Khudafi, A.M., Ba-Jaalah, K.S., 2019. Hybrid artificial intelligent approach for choke size estimation in volatile and black oil reservoirs. In: Paper Presented at the 2019 First International Conference of Intelligent Computing and Engineering (ICOICE) Held at Hadhramout. https://doi.org/10.1109/ICOICE48418.2019.9035198. Yemen, Yemen on the 15 &16 December, 2019.

Adeyemi, H.O., Jagun, Z.O.O., Giwa, S.O., Adetunji, O.R., Owamoyo, R.A., 2016. Modelling room cooling capacity with fuzzy logic procedure. Nigerian Journal of Technology (NIJOTECH) 35 (3), 519–526.

Amaechi, U.C., Ikpeka, P.M., Xianlin, M., Ugwu, J.O., 2019. Application of machine learning models in predicting initial gas production rate from tight gas reservoirs. The Mining-Geology-Petroleum Engineering Bulletin 29–40.

Achong, I., 1961. Revised Bean Performance Formula for Lake Maracaibo Wells, Internal Co. Report. Shell Oil Co., Houston, Texas.

Ahmadi, M.A., Ebadi, M., Shokrollahi, A., Majidic, S.M.J., 2013. Evolving artificial neural network and imperialist competitive algorithm for prediction oil flow rate of the reservoir. Appl. Soft Comput. 13 (2), 1085–1098. https://doi.org/10.1016/j.asoc.2012.10.009.

Akbar, A.M., 1978. A statistical correlation for predicting oil and gas flow rates through chokes. J. Univ. Kuwait (Sci.) 5, 1978.

Al-Ajmi, M.D., Alarifi, S.A., Mahsoon, A.H., 2015. Improving Multiphase Choke Performance Prediction and Well Production Test Validation Using Artificial Intelligence: A New Milestone. Paper SPE 173394 MS Presented at the SPE Digital Energy Conference and Exhibition Held in the Woodlands. Texas, USA, 3 – 5 March 2015.

Al-Attar, H.H., Abdul-Majeed, G.H., 1988. Revised bean performance equation for East baghdad oil wells. SPE Prod. Eng. 3 (1), 127–131. https://doi.org/10.2118/13742-PA.

Al-Attar, H., 2008. Performance of wellhead chokes during sub-critical flow of gas condensates. J. Petrol. Sci. Eng. 60, 205–212.

Al-Attar, H.H., 2009. New correlations for critical and subcritical two phase flow through surface chokes in high rate oil wells. In: Paper SPE 120788 Presented at the 2009 SPE Latin American and Caribbean Petroleum Engineering Conference Held in Cartagena. Colombia, 31 May – 3 June 2009.

Alavi, A.H., Ameri, M., Gandomi, A.H., Mirzahosseini, M.R., 2011. Formulation of flow number of asphalt mixes using a hybrid computational method. Construct. Build. Mater. 25, 1338–1355. Number 3.

Alexander, D.L.J., Tropsha, A., Winkler, D.A., 2015. Beware of R^2: simple, unambiguous assessment of the prediction accuracy of QSAR and QSPR models. J. Chem. Inf. Model. 55 (7), 1316–1322.

Alimonti, C., Falcone, G., Bello, O., 2010. Two-phase flow characteristics in multiple orifice valves. Exp. Therm. Fluid Sci. 34, 1324–1333.

Al Kadem, M., Al Dabbous, M., Al Mashhad, A., Al Sadah, H., 2019. Utilization of artificial neural networking for real-time oil production rate estimation. In: Paper SPE -197879-MS Presented at the Abu Dhabi International Petroleum Exhibition & Conference, 11-14 November, 2019. https://doi.org/10.2118/197879-MS. Abu Dhabi, UAE.

Al-Khalifa, M.A., Al-Marhoun, M.A., 2013. Application of neural network for two-phase flow through chokes. In: Paper SPE 169597 Presented at the SPE Saudi Arabia Section Annual Technical Symposium and Exhibition Held in Khobar. Saudi Arabia, 19–22 May 2013.

Al-Qutami, T.A., Ibrahim, R., Ismail, I., Ishak, M.A., 2017a. Radial basis function network to predict gas flow rate in multiphase flow. In: Proceedings of the 9th International Conference on Machine Learning and Computing Held at Singapore from February 24-26, 2017, pp. 141–146. https://doi.org/10.1145/3055635.3056638.

Al-Qutami, T.A., Ibrahim, R., Ismail, I., Ishak, M.A., 2017b. Development of soft sensor to estimate multiphase flow rates using neural networks and early stopping. Int. J. Smart Sens. Intell. Syst. 10 (1), 199–222.

Al-Qutami, T.A., Ibrahim, R., Ismail, I., Ishak, M.A., 2018. Virtual multiphase flow metering using diverse neural network ensemble and adaptive simulated annealing. Expert Syst. Appl. 93 (1), 72–85. https://doi.org/10.1016/j.eswa.2017.10.014.

Al-Rumah, M., Alenezi, R.A., 2019. New universal two-phase choke correlations developed using non-linear multivariable optimization technique. Journal of Engineering Research 7 (3), 320–329.

Al-Rumah, M., Aladwani, F., Alatefi, S., 2020. Toward the development of a universal choke correlation – global optimization and rigorous computational techniques. Journal of Engineering Research 8 (Number 3), 240–254.

Al-Rumah, M., Bizanti, M., 2007. New Choke Correlation for Sabriyah Field Kuwait, Paper SPE 105103 Presented at the 2007 Middle East Oil and Gas Show and Conference, Bahrain, 11-14 March. Society of Petroleum Engineers.

Al-Safran, E.M., Kelkar, M., 2009. Predictions of two-phase critical flow boundary and mass-flow rate across chokes. In: Paper SPE 109243 Presented at the SPE Annual Technical Conference and Exhibition. Anaheim, California, 11 – 14 November 2007.

Al-Shammari, A., 2011. Accurate prediction of pressure drop in two phase vertical flow systems using artificial intelligence. In: Paper SPE 149035 Presented at the SPE/DGS Saudi Arabia Section Technical Symposium and Exhibition Held in Al-Khobar, Saudi Arabia, 15 – 18 May 2011.

Al-Towailib, A., Al-Marhoun, M.A., 1994. A new correlation for two-phase flow through chokes. J. Can. Pet. Technol. 33 (5), 40–43.

Amin, A., 2015. Evaluation of commercially available virtual flow meters (VFMs). In: Offshore Technology Conference. https://doi.org/10.4043/25764-MS. USA, May 4, 2015.

Andrianov, N., 2018. A machine learning approach for virtual flow metering and forecasting. In: Proceedings of the 3rd IFAC Workshop on Automatic Control in Offshore Oil and Gas Production, Esbjerg, Denmark. May 30–June 01, 2018.

Anifowose, F.A., 2011. Artificial intelligence application in reservoir characterization and modeling: whitening the black box. In: Paper SPE 155413 Presented at the SPE Saudi Arabia Section Young Professionals Technical Symposium Held in Dhahran. Saudi Arabia.

Anifowose, F.A., Labadin, J., Abdulraheem, A., 2017. Hybrid intelligent systems in petroleum reservoir characterization and modeling: the journey so far and the challenges ahead. Journal of Petroleum Exploration and Production Technology 7, 251–263. https://doi.org/10.1007/s13202-016-0257-3.

API, 2005. API Recommended Practice for Measurement of Multiphase Flow, 2005. API Publishing Services, p. 1220. L.

Archontoulis, S.V., Miguez, F.E., 2015. Nonlinear regression models and applications in agricultural research. Agron. J. 107 (2) https://doi.org/10.2134/agronj2012.0506.

Ashford, F.E., 1974. An evaluation of critical multiphase flow performance through wellhead chokes. J. Petrol. Technol. 26, 843–850.

Ashford, F.E., Pierce, P.E., 1975. Determining multiphase pressure drops and flow capacities in downhole safety valves. J. Petrol. Technol. 27, 1145–1152.

Aslam, F., Farooq, F., Amin, M.N., Khan, K., Waheed, A., Akbar, A., Javed, M.F., Alyousef, R., Alabdulijabbar, H., 2020. Applications of gene expression programming for estimating compressive strength of high-strength concrete. Adv. Civ. Eng. 2020, 1–23. https://doi.org/10.1155/2020/8850535. Article ID 8850535.

Baghban, A., Abbasi, P., Rostami, P., Bahadori, M., Ahmad, Z., Kashiwao, T., Bahadori, A., 2016. Estimation of oil and gas properties in petroleum production and processing operations using rigorous model. Petrol. Sci. Technol. 34 (13), 1129–1136. https://doi.org/10.1080/10916466.2016.1183028.

Bahrami, B., Mohsenpour, S., Noghabi, H.R.S., Hemmati, N., Tabzar, A., 2019. Estimation of flow rates of individual phases in an oil-gas-water multiphase flow system using neural network approach and pressure signal analysis. Flow Meas. Instrum. 66, 28–36. https://doi.org/10.1016/j.flowmeasinst.2019.01.018.

Bairamzadeh, S., Ghanaatpisheh, E., 2015. A new choke correlation to predict liquid flow rate. Sci. Int. 27 (1), 271–274.

Baroczy, C.J., 1961. A systemic correlation for two-phase pressure drop. Chem. Eng. Prog. Symp. Ser. 62, 232–249.

Baxendell, P.B., 1958. Producing wells on casing flow – an analysis of flowing pressure gradients. AIME 213, 202–207.

Beck, A., Kurz, M., 2020. A Perspective on Machine Learning Methods in Turbulence Modelling. Preprint submitted to the Journal of Latex templates, pp. 1–38.

Behnoud far, P., Hosseini, P., 2017. Estimation of lost circulation amount occurs during under balanced drilling using drilling data and neural network. Egyptian Journal of Petroleum 26 (3), 627–634.

Beiranvand, M.S., Mohammadmoradi, P., Aminshahidy, B., Fazelabdolabadi, B., Aghahoseini, S., 2012. New multiphase choke correlations for a high flow rate Iranian oil field. Mech. Sci. 3, 43–47.

Beiranvand, M.S., Khorzoughi, M.B., 2012. Introducing a new correlation for multiphase flow through surface chokes with newly incorporated parameters. SPE Prod. Oper. 27 (4), 422–428.

Bello, O., Ade-Jacob, S., Yuan, K., 2014. Development of hybrid intelligent system for virtual flow metering in production wells. In: Paper SPE-167880-MS Presented at the SPE Intelligent Energy Conference & Exhibition. https://doi.org/10.2118/167880-MS, 1-3 April, Utrecht, The Netherlands.

Benlizidia, I., 2009. Multiphase flow meter used in production testing in heavy oil and extra heavy oil in Colombia. In: 10th Simposio Bolivariano-Exploracion Petrolera en las Cuencas Subandinas.

Berneti, S.M., Shahbazian, M., 2011. An imperialist competitive algorithm artificial neural network method to predict oil flow rate of the wells. Int. J. Comput. Appl. 26 (10), 47–50.

Bhattacharjya, R.K., 2012. Introduction to genetic algorithms. IIT Guwahati. Available: http://www.iitg.ernet.in/rkbc/CE602/CE602/Genetic%20Algorithms.pdf. (Accessed 13 April 2021).

Bikmukhametov, T., Jäschke, J., 2020a. First principles and machine learning virtual flow metering: a literature review. J. Petrol. Sci. Eng. 184 (2020), 106487.

Bikmukhametov, T., Jäschke, J., 2020b. Combining machine learning and process engineering physics towards enhanced accuracy and explainability of data-driven models. Comput. Chem. Eng. 138, 12 July 2020, 106834.

Bilgili, M., Sahin, B., 2010. Comparative analysis of regression and artificial neural network models for wind speed prediction. Meteorol. Atmos. Phys. 109 (1), 61. https://doi.org/10.1007/s00703-010-0093-9.

Bokhamseen, S.H., Tarihoran, A.R., Al-Baqawi, A.M., Al-Malki, B.H., 2015. Utilization of numerical optimization to model gas condensate flow through chokes in a rich gas condensate reservoir in Saudi Arabia. In: Paper SPE 177694 Presented at the Abu Dhabi International Petroleum Exhibition and Conference Held in Abu Dhabi, UAE, 9 – 12 November 2015.

Bonfitto, A., Feraco, S., Tonoli, A., Amati, N., Monti, F., 2019. Estimation accuracy and computational cost analysis of artificial neural networks for state of charge estimation in lithium batteries. Batteries 5 (47), 1–17.

Buffa, F.K., Baliño, J.L., 2017. Review of multiphase flow models for choke valves. Journeys in Multiphase Flows (JEM2017) March 27-31, 2017 - São Paulo 41, 1–12. Brazil.

Buhulaigah, A., Al-Mashhad, A.S., Al-Arifi, S.A., Al-Kadem, M.S., Al-Dabbous, M.S., 2017. Multilateral wells evaluation utilizing artificial intelligence. In: Paper SPE-183688-MS Presented at the SPE Middle East Oil & Gas Show and Conference, 6-9 March, Manama, Kingdom of Bahrain. https://doi.org/10.2118/183688-MS.

Castillo, O., Melin, P., 2001. Fuzzy logic. In: Soft Computing for Control of Non-linear Dynamical Systems. Studies in Fuzziness and Soft Computing, vol. 63. Physica, Heidelberg. https://doi.org/10.1007/978-3-7908-1832-1_2.

Chaabene, W.B., Flah, M., Nehdi, M.L., 2020. Machine learning prediction of mechanical properties of concrete: critical review. Construct. Build. Mater. 260, 1–18.

Chapra, S.C., Canale, R.P., 2010. Numerical Methods for Engineers, sixth ed. McGraw-Hill, New York, p. 994.

Cheng, R., 2007. Genetic Algorithms and Engineering Design. Wiley, Hoboken, NJ, USA, 2007.

Chisholm, D., 1983. Two Phase Flow in Pipelines and Heat Exchangers. George Godwin, London.

Choubineh, A., Ghorbani, H., Wood, D.A., Moosavi, S.R., Khalafi, E., Sadatshojaei, E., 2017. Improved predictions of wellhead choke liquid critical-flow rates: modelling based on hybrid neural network training learning based optimization. Fuel 207, 547–560.

Christou, V., Tsipouras, M.G., Giannakeas, N., Tzallas, A.T., Brown, G., 2019. Hybrid extreme learning machine approach for heterogeneous neural networks. Neurocomputing 361, 137–150. https://doi.org/10.1016/j.neucom.2019.04.092, 2019.

Corneliussen, S., Couput, J.P., Dahl, E., Dykesteen, E., Frøysa, K.E., Malde, E., Moestue, H., Moksnes, P.O., Scheers, L., Tunheim, H., 2005. Handbook of Multiphase Flow Metering; Revision 2. Norwegian Society for Oil and Gas Measurement (NFOGM), Oslo, Norway, 2005.

Dave, A.J., Manera, A., 2020. Inference of Gas-liquid Flowrate Using Neural Networks. Preprint Submitted to International Journal of Multiphase Flow. ArXiv, abs/2003. https://arxiv.org/pdf/2003.08182.pdf, 08182.

Demuth, H., Beale, M., Martin, H., 2009. Neural Network Toolbox Users Guide. The Mathworks, Inc, p. 906, Version 6.

Denney, D., 1998. Multiphase-flowmeter experience. J. Petrol. Technol. 50 (4), 84–86. https://doi.org/10.2118/0498-0084-JPT.

Donthi, R., Praveen, J.P., Prasad, S.V., Mahaboob, B., Venkateswarlu, B., 2019. Numerical techniques of nonlinear regression model estimation. Recent trends in pure and applied mathematics. AIP Conference Proceedings 2177, 020082. https://doi.org/10.1063/1.5135257, 2019.

Dou, T., Lopes, Y.K., Rockett, P., 2018. GPML: an XML-Based Standard for the Interchange of Genetic Programming Trees. Technical Report No. CR2018-2r2 Submitted to the Department of Electronic and Electrical Engineering. University of Sheffield, UK.

Downton, G.C., 2012. Challenges of modeling drilling systems for the purposes of automation and control. In: Proceedings of the 2012 IFAC Workshop on Automatic Control in Offshore Oil and Gas Production May 31 - June 1, 2012, pp. 201–210. Trondheim, Norway.

Dutta, P., Kumar, A., 2020. Modeling and optimization of a liquid flow process using an artificial neural network-based flower pollination algorithm. J. Intell. Syst. 29 (1), 787–798. https://doi.org/10.1515/jisys-2018-0206.

El-Banbi, A., Alzahabi, A., El-Maraghi, A., 2018. Black Oils. PVT Property Correlations 147, 182. https://doi.org/10.1016/b978-0-12-812572-4.00007-2.

Elgibaly, A.A.M., Nashawi, I.S., 1998. New correlations for critical and subcritical two-phase flow through wellhead chokes. J. Can. Pet. Technol. 37 (6).

Elhaj, M.A., Anifowose, F., Abdulraheem, A., 2015. Single gas flow prediction through chokes using artificial intelligence techniques. In: Paper SPE 177991 MS Presented at the SPE Saudi Arabia Section Annual Technical Symposium and Exhibition Held in Al-Khobar, Saudi Arabia, 21 – 23 April 2015.

Fahim, M.A., Akbar, A.M., Shaban, H., 1978. Theoretical approach to two phase flow of oil and gas through chokes. In: Paper SPE 7904 Presented at the International Conference of Chemical Engineering (CHISA) Held in Prague between August 20 – 25, 1978.

Falcone, G., Hewitt, G., Alimonti, C., 2009. Multiphase Flow Metering: Principles and Applications, vol. 54. Elsevier, Amsterdam, The Netherlands, 2009.

Falcone, G., Hewitt, G., Alimonti, C., Harrison, B., 2001. Multiphase flow metering: current trends and future developments. In: Paper SPE-71474-MS Presented at the SPE Annual Technical Conference and Exhibition, 30 September-3 October. https://doi.org/10.2118/71474-MS. New Orleans, Louisiana.

Fazeli, H., Soleimani, R., Ahmadi, M.A., Badrnezhad, R., Mohammadi, A.H., 2013. Experimental study and modelling of ultrafiltration of refinery effluents using a hybrid intelligent approach. Journal of Energy and Fuels 27 (6), 3523–3537.

Ferreira, C., 2001. Gene expression programming: a new adaptive algorithm for solving problems. Complex Syst. 13 (2), 87–129. https://arxiv.org/ftp/cs/papers/0102/0102027.pdf. (Accessed 13 April 2021).

Fortunati, F., 1972. Two phase flow through wellhead chokes. In: Paper SPE 3742 Presented at the SPE-European Spring Meeting Held in Amsterdam. The Netherlands, May 16 – 18, 1972.

Fuladgar, A.M., Vatani, Z., 2019. New empirical correlation for oil flowrate prediction through chokes. J. Serb. Chem. Soc. 84, 1–11. https://doi.org/10.2298/JSC190520110F.

Ganat, T.A., Hrairi, M., 2018. A new choke correlation to predict flow rate of artificially flowing wells. J. Petrol. Sci. Eng. 171, 1378–1389.

Geng, Y., Zheng, J., Shi, G., 2006. Measurement of two-phase flow rate based on slotted orifice couple and neural network ensemble. In: Proceedings of the 2006 IEEE International Conference on Information Acquisition August 20 - 23, 2006. Weihai, Shandong, China.

Ghadam, A.G.J., Kamali, V., 2015. Prediction of gas critical flow rate for continuous lifting of liquids from gas wells using comparative neural fuzzy inference system. Journal of Applied Environmental and Biological Sciences 5 (8S), 196–202, 2015.

Ghareeb, M., Shedid, S.A., 2007. A new correlation for calculating wellhead production considering influences of temperature, GOR, and water-cut for artificially lifted wells. In: Paper IPTC 11101 Presented at the International Petroleum Technology Conference Held in Dubai, U.A.E., 4–6 December 2007.

Ghorbani, H., Moghadasi, J., Wood, D.A., 2017. Prediction of gas flow rates from gas condensate reservoirs through wellhead chokes using a firefly optimization algorithm. J. Nat. Gas Sci. Eng. 45 (2017), 256–271.

Ghorbani, H., Wood, D.A., Choubineh, A., Tatar, A., Abarghoyi, P.G., Madani, M., Mohamadian, N., 2018. Prediction of oil flow rate through an orifice flow meter: artificial intelligence alternatives compared. Petroleum 6 (4), 404–414. https://doi.org/10.1016/j.petlm.2018.09.003.

Ghorbani, H., Wood, D.A., Moghadasi, J., Choubineh, A., Abdizadeh, P., Mohamadian, N., 2019. Predicting liquid flow-rate performance through wellhead chokes with genetic and solver optimizers: an oil field case study. Journal of Petroleum Exploration and Production Technology 9, 1355–1373. https://doi.org/10.1007/s13202-018-0532-6.

Gilbert, W.E., 1954. Flowing and gas-lift well performance. API Drilling and Production Practice 126–157, 1954.

Goodman, E.D., 2009. Introduction to Genetic Algorithms. Presentation at the 2009 World Summit on Genetic and Evolutionary Computation Shanghai, China. https://www.egr.msu.edu/~goodman/GECSummitIntroToGA_Tutorial-goodman.pdf. (Accessed 13 April 2021).

Gorjaei, R.G., Songolzadeh, R., Torkaman, M., Safari, M., Zargar, G., 2015. A novel PSO-LSSVM model for predicting liquid rate of two phase flow through wellhead chokes. J. Nat. Gas Sci. Eng. 24, 228–237.

Grigg, R.B., 2015. CO_2 applications in technology focus. J. Petrol. Technol. 67, 114, 7.

Grolmes, M.A., Leung, J.C., 1985. Chem. Eng. Prog. 81, 47, 8.

Hansen, L.S., Pedersen, S., Durdevic, P., 2019. Multi-phase flow metering in offshore oil and gas transportation pipelines: trends and perspectives. Sensors 2019 19, 2184. https://doi.org/10.3390/s19092184.

Hasanvand, M., Berneti, S.M., 2015. Predicting oil flow rate due to multiphase flow meter by using an artificial neural network. Energy Sources, Part A Recovery, Util. Environ. Eff. 8 (37), 840–845. https://doi.org/10.1080/15567036.2011.590865.

Hassan, A., Elkatatny, S., Abdulraheem, A., 2019. Application of artificial intelligence techniques to predict the well productivity of fishbone wells. Sustainability Journal 11, 1–14, 6083.

Hassan, A., Mahmoud, M., Al-Majed, A., Abdulraheem, A., 2020. A new technique to quantify the productivity of complex wells using artificial intelligence tools. In: Paper IPTC-19706 Presented at the International Petroleum Technology Conference, 13-15 January, Dhahran, Kingdom of Saudi Arabia. https://doi.org/10.2523/IPTC-19706.

Hayes, A., 2021. Multiple Linear Regression (MLR), 01/04/2021. https://www.investopedia.com/terms/m/mlr.asp.

Haykin, S., 1999. Neural Networks, a Comprehensive Foundation, second ed. Prentice Hall Inc., Upper Saddle River.

Helmy, T., Anifowose, F., 2010. Hybrid computational intelligence models for porosity and permeability prediction of petroleum reservoirs. Int. J. Comput. Intell. Appl. 9 (4), 313–337. https://doi.org/10.1142/S1469026810002902.

Hemmati-Sarapardeh, A., Larestani, A., Amar, M.N., 2020. Weaknesses and Strengths of Intelligent Models in Petroleum Industry *in* Applications of Artificial Intelligence Techniques in the Petroleum Industry. Gulf Professional Publishing, p. 322.

Henry, R., Fauske, H., 1971. The two phase critical flow of one component mixtures in nozzles, orifices and short tubes. ASME Journal of Heat Transfer 93, 179–187.

Hotvedt, M., Grimstad, B., Imsland, L., 2020. Developing a hybrid data-driven, mechanistic virtual flow meter - a case study. Paper accepted by IFAC for publication 53 (2), 2–6. https://arxiv.org/abs/2002.02737.

Huang, Z., Li, X., Ji, H., Wang, B., Li, H., 2009. Oil-water two-phase flow measurement based on a hybrid flowmeter and dominant phase identification. In: I2MTC 2009 - International Instrumentation and Measurement Technology Conference. Singapore, 5-7 May 2009.

James, G., Witten, D., Hastie, T., Tibshirani, R., 2013. An Introduction to Statistical Learning. Springer, New York, New York.

Jeshvaghani, P.A., Feghhi, S.A.H., Khorsandi, M., 2019. Temperature independent flow-rate prediction in two-phase flow loop using gamma-ray attenuation and Artificial Neural Networks. Radiat. Meas. 128, 1–7.

Johnson, R., 2017. Data Science: Back to Basics – It's about Being Flexible. https://spr.com/data-science-back-basics-flexible/#:~:text=A%20model%20has%20to%20walk,a%20model%20determines%20this%20balance. (Accessed 22 November 2020).

Jumaah, H.A., 2019. Modify chock performance equation for tertiary reservoir wells in khabaz oil field. 1st international conference on petroleum technology and petrochemicals. IOP Conf. Ser. Mater. Sci. Eng. 579, 012023, 2019.

Kakar, K., 2018. Artificial Neural Network Modeling of Well Performance in the Garrington Field. University of Calgary, Calgary, AB. Cardium Formation (Unpublished master's thesis). http://hdl.handle.net/1880/109399.

Kalam, S., Khan, M.R., Tariq, Z., Siddique, F.A., Abdulraheem, A., Khan, R.A., 2019. A novel correlation to predict gas flow rates utilizing artificial intelligence: an industrial 4.0 approach. In: Paper SPE-201170-MS Presented at the SPE/PAPG Pakistan Section Annual Technical Symposium and Exhibition Held in Islamabad, Pakistan, 18 – 20 November 2019.

Kalechofsky, H., 2016. A Simple Framework for Building Predictive Models. A Little Data Science Business Guide. MSquared Consulting, A Solomon Edwards Company, pp. 1–18.

Kargarpour, M.A., 2019. Oil and gas well rate estimation by choke formula: semi-analytical approach. Journal of Petroleum Exploration and Production Technology (9), 2375–2386. https://doi.org/10.1007/s13202-019-0629-6, 2019.

Kayacan, E., Khanesar, M.A., 2016. Chapter 2 - Fundamentals of Type-1 Fuzzy Logic Theory. Fuzzy Neural Networks for Real Time Control Applications. Concepts, Modeling and Algorithms for Fast Learning, pp. 13–24. https://doi.org/10.1016/B978-0-12-802687-8.00002-5.

Kaydani, H., Najafzadeh, M., Mohebbi, A., 2014. Wellhead choke performance in oil well pipeline systems based on genetic programming. J. Pipeline Syst. Eng. Pract. 5 (3), 1–4.

Kenton, W., 2020. Defining Nonlinear Regression, 01/04/2021. https://www.investopedia.com/terms/n/nonlinear-regression.asp.

Khamis, M., Elhaj, M., Abdulraheem, A., 2020. Optimization of choke size for two-phase flow using artificial intelligence. Journal of Petroleum Exploration and Production Technology 10, 487–500. https://doi.org/10.1007/s13202-019-0734-6.

Khan, M.R., Tariq, Z., Abdulraheem, A., 2020. Application of artificial intelligence to estimate oil flow rate in gas-lift wells. In: Natural Resources Research. 2020 International Association for Mathematical Geosciences. https://doi.org/10.1007/s11053-020-09675-7.

Khan, M.R., Alnuaim, S., Tariq, Z., Abdulraheem, A., 2019. Machine learning application for oil rate prediction in artificial gas lift wells. In: Paper SPE-194713-MS Presented at the SPE Middle East Oil and Gas Show and Conference, 18-21 March, Manama, Bahrain. https://doi.org/10.2118/194713-MS.

Khorzoughi, M.B., Beiranvand, M.S., Rasaei, M.R., 2013. Investigation of a new multiphase flow choke correlation by linear and non-linear optimization methods and Monte Carlo sampling. Journal of Petroleum Exploration and Production Technology 3, 279–285.

Koza, J.R., 1992. Genetic Programming: on the Programming of Computers by Means of Natural Selection. MIT Press, Cambridge, MA, USA, 1992.

Kronberger, G., 2010. Symbolic Regression for Knowledge Discovery Bloat, Overftting, and Variable Interaction Networks. Johannes Kepler Universitat, Austria. Ph.D. Dissertation. Technisch-Naturwissenschaftliche Fakultat.

Kuhn, M., Johnson, K., 2019. Feature Engineering and Selection: A Practical Approach for Predictive Models, first ed. CRC Press, Taylor and Francis Group, A Chapman & Hall Book, p. 298.

Lak, A., Azin, R., Osfouri, S., Fatehi, R., 2017. Modeling critical flow through choke for a gas-condensate reservoir based on drill stem test data. Iranian Journal of Oil & Gas Science and Technology 6 (Number 3), 29–40.

Lawson, D., Marion, G., 2008. An Introduction to Mathematical Modelling. https://people.maths.bris.ac.uk/~madjl/course_text.pdf. (Accessed 11 April 2021).

Leal, J., Al-Dammen, M., Villegas, R., Bolarinwa, S., Aziz, A., Azly, A., Buali, M., Garzon, F., 2013. A new analytical model to predict gas rate volume measurement through well head chokes. In: Paper IPTC 17046 Presented at the International Petroleum Technology Conference Held in Beijing, China, 26 – 28 March 2013.

Li, S., Zhao, F., Zheng, X., He, D., Bai, B., 2020. Wet gas metering by cone throttle device with machine learning. Measurement 164, 1–11. https://doi.org/10.1016/j.measurement.2020.108080.

Lima, N.N.M., Linan, L.Z., Melo, D.N.C., Manenti, F., Filho, R.M., Marcelo Embiruçu, M., Maciel, M.R.W., 2015. Nonlinear fuzzy identification of batch polymerization processes. Computer Aided Chemical Engineering 37, 599–604. https://doi.org/10.1016/B978-0-444-63578-5.50095-5.

Liu, J., Chen, J., Chen, Z., 2008. Critical flashing flow in convergent–divergent nozzles with initially subcooled liquid. Int. J. Therm. Sci. 47 (8), 1069–1076.

Liu, X., Lao, L., Falcone, G., 2020. A comprehensive assessment of correlations for two-phase flow through Venturi tubes. J. Nat. Gas Sci. Eng. 78 (2020), 103323.

Liu, Z., Li, H., 2005. A probabilistic fuzzy logic system for modeling and control. IEEE Trans. Fuzzy Syst. 13 (6), 848–859.

Liu, W.Z., 2016. Multiphase Flow Meter. U.S. Patent 14/716,323, 19 May 2016.

Lockhart, R.W., Martenelli, R.C., 1949. Proposed correlation of data for isothermal two phase data two component flow in pipes. Chem. Eng. Prog. 45, 681–705.

Lujala, P., Rustad, S.A., Le Billon, P., 2017. Has the EITI Been Successful? Reviewing Evaluations of the Extractive Industries Transparency Initiative, vol. 5. U4 Brief, pp. 1–8.
Mahmud, H.B., Abdullah, A., 2017. Investigate a gas well performance using nodal analysis. IOP Conf. Ser. Mater. Sci. Eng. 217 (2017), 012022 https://doi.org/10.1088/1757-899X/217/1/012022.
Marfo, S.A., Kporxah, C., 2020. Predicting Oil Production Rate Using Artificial Neural Network and Decline Curve Analytical Methods. Proceedings of 6th UMaT Biennial International Mining and Mineral Conference, Tarkwa, Ghana, pp. 43–50.
Marshall, C., Thomas, A., 2015. Maximising economic recovery - a review of well test procedures in the North Sea. In: Paper SPE-175518-MS Presented at the SPE Offshore Europe Conference and Exhibition, 8-11 September, Aberdeen, Scotland, UK. https://doi.org/10.2118/175518-MS.
Mekanik, F., Imteaz, M., Gato-Trinidad, S., Elmahdi, A., 2013. Multiple regression and artificial neural network for long term rainfall forecasting using large scale climate modes. J. Hydrol. 503 (2), 11–21.
Meribout, M., Azzi, A., Ghendour, N., Kharoua, N., Khezzar, L., AlHosani, E., 2020. Multiphase flow meters targeting oil and gas industries. Measurement 165. https://doi.org/10.1016/j.measurement.2020.108111.
Meribout, M., Al-Rawahi, N., Al-Naamany, A., Al-Bimani, A., Al-Busaidi, K., Meribout, A., 2009. A non-radioactive flow meter using a new hierarchical neural network. In: Paper BHR-2009-B2 Presented at the 14th International Conference on Multiphase Production Technology, 17-19 June, Cannes, France.
Meribout, M., Al-Rawahi, N.Z., Al-Naamany, A.M., Al-Bimani, A., Al-Busaidi, K., Meribout, A., 2010. A multisensor intelligent device for real-time multiphase flow metering in oil fields. IEEE Transactions on Instrumentation and Measurement 59 (6), 1507–1519.
Mesallati, A., Bizanti, M., Mansouri, M., 2000. Multiphase-flow choke correlations for offshore bouri oil field. In: Proceedings of the International Gas Union 21st World Gas Conference. Nice, France, 6–9 June 2000.
Miłkowski, M., Hensel, W.M., Hoho, M., 2018. Replicability or reproducibility? On the replication crisis in computational neuroscience and sharing only relevant detail. J. Comput. Neurosci. 45, 163–172. https://doi.org/10.1007/s10827-018-0702-z.
Mirzaei-Paiaman, A., 2013. An empirical correlation governing gas condensate flow through chokes. Petrol. Sci. Technol. 31 (4), 368–379. https://doi.org/10.1080/10916466.2010.529552.
Mirzaei-Paiaman, A., Salavati, S., 2013. A new empirical correlation for sonic simultaneous flow of oil and gas through wellhead chokes for Persian oil fields. Energy Sources, Part A Recovery, Util. Environ. Eff. 9 (35), 817–825. https://doi.org/10.1080/15567031003773304.
Mitchell, M., 1995. Genetic algorithms: an overview. Complexity 1 (Number 1), 31–39.
Moghaddasi, M.J., Lotfi, I., Moghaddasi, M., 2015. Comparison of correlations for predicting oil flow rate passing through chokes. Energy Sources, Part A Recovery, Util. Environ. Eff. 37, 1340–1345, 2015.
Mohammadmoradi, P., Moradi, H.M., Kantzas, A., 2018. Data-Driven production forecasting of unconventional wells with Apache spark. In: Paper SPE-190098-MS Presented at the SPE Western Regional Meeting, 22-26 April, Garden Grove, California, USA. https://doi.org/10.2118/190098-MS.
Mokhtari, K., Waltrich, P.J., 2016. Performance evaluation of multiphase flow models applied to virtual flow metering. Proceedings of the 11th International Conference on Engineering Sciences (AFM 2016), WIT Transactions on Engineering Sciences 105.
Moody, F.J., 1965. Maximum flow rate of a single-component, two-phase mixture. J. Heat Tran. 87, 134–142.
Mwalyepelo, J.Y., 2015. Analysis of Selected Multiphase Metering Concepts. Masters degree thesis submitted to the Department of Petroleum Engineering and Applied Geophysics, Norwegian University of Science and Technology, Norway.
Mwalyepelo, J., Stanko, M., 2016. Improvement of multiphase flow rate model for chokes. J. Petrol. Sci. Eng. 145, 321–327, 2016.
Naseri, S., Tatar, A., Shokrollahi, A., 2017. Development of an accurate method to prognosticate choke flow coefficients for natural gas flow through nozzle and orifice type chokes. Flow Meas. Instrum. 48, 1–7, 2016.
Nasriani, H.R., Kalantari Asl, A., 2011. Two-phase flow choke performance in high rate gas condensate wells. In: Paper SPE 145576 Presented at the SPE Asia Pacific Oil and Gas Conference and Exhibition Held in Jakarta, Indonesia 20 – 22 September 2011.
Nasriani, H.R., Kalantari Asl, A., 2015. Choke performance in high-rate gas condensate wells under subcritical flow condition. Energy Sources, Part A Recovery, Util. Environ. Eff. 37 (2), 192–199. https://doi.org/10.1080/15567036.2011.582607.
Nasriani, H.R., Khan, K., Graham, T., Ndlovu, S., Nasriani, M., Mai, J., Rafiee, M.R., 2019. An investigation into sub-critical choke flow performance in high rate gas condensate wells. Energies 12, 1–18.
Nazari, N., Alshafloot, T., 2019. Prediction of Two Phase Flow Rate through Wellhead Chokes in Oil Wells. CS229 Final Project Report. Stanford University. http://cs229.stanford.edu/proj2019aut/data/assignment_308875_raw/26487906.pdf.
NEITI, 2015. Final Report on the Financial, Physical and Process Audit of the Nigeria Oil and Gas Industry: an Independent Report Assessing and Reconciling Physical and Financial Flows within Nigeria's Oil and Gas Industry. OGA 2015 report, p. 203. https://neiti.gov.ng/index.php/neiti-audits/oil-and-gas.
Nejatian, I., Kanani, M., Arabloo, M., Bahadori, A., Zendehboudi, S., 2014. Prediction of natural gas flow through chokes using support vector machine algorithm. J. Nat. Gas Sci. Eng. 18, 155–163.
Nind, T.E.W., 1964. Principle of Oil Well Production. McGraw-Hill Book Company, pp. 133–204.
Obukhowo, E.C., Wilfred, O.C., Appah, D., Umeleuma, M.B., 2015. Modelling of multiphase flow metering for crude oil production monitoring. International Journal of Current Engineering and Technology 5 (4), 2935–2941.
Oddie, G., Pearson, J.R.A., 2004. Flow-rate measurement in two-phase flow. Annu. Rev. Fluid Mech. 36, 149–172.
Okon, A.N., Appah, D., 2016. Neural network models for predicting wellhead pressure-flow rate relationship for Niger delta oil wells. Journal of Scientific Research & Reports 12 (1), 1–14.
Okon, A.N., Udoh, F.D., Appah, D., 2015. Empirical wellhead pressure – production rate correlations for Niger Delta oil wells. In: Paper SPE 178303 Presented at the Nigeria Annual International Conference and Exhibition Held in Lagos, Nigeria, 4 – 6 August 2015.
Omana, R., Houssier, C., Brown, K.E., Brill, J.P., Thompson, R.E., 1968. Multiphase Flow through Chokes, Paper SPE 2682 Presented at the 1969 SPE Annual Meeting. Denver Colorado from 28th September to 1st October.
Omana, R., Houssiere Jr., C., Brown, K.E., Brill, J.P., Thompson, R.E., 1969. Multiphase flow through chokes. In: Fall Meeting of the Society of Petroleum Engineers of AIME.
Omrani, P.S., Dobrovolschi, I., Belfroid, S., Kronberger, P., Munoz, E., Noordzee, W., 2018. Improving the accuracy of virtual flow metering and back allocation through machine learning. In: Paper SPE – 192819 – MS Presented at the Abu Dhabi International Petroleum Exhibition and Conference Held in Abu Dhabi, UAE, 12 – 15 November 2018.
Osman, M.E., Dokla, M.E., 1990. Gas condensate flow through chokes. In: Paper SPE 20988 MS Presented at the European Petroleum Conference, 21-24 October, The Hague, Netherlands.
Patel, P., Odden, H., Djoric, B., Garner, R.D., Vea, H.K., 2014. Model based multiphase metering and production allocation. In: Paper OTC-25457-MS Presented at the Offshore Technology Conference-Asia. https://doi.org/10.4043/25457-MS, 25-28 March, Kuala Lumpur, Malaysia.
Perkins, T.K., 1990. Critical and subcritical flow of multiphase mixtures through chokes. In: Paper SPE 20633 Presented at the SPE 65th Annual Technical Conference and Exhibition. New Orleans, LA, September 23-26.
Perkins, T.K., 1993. Critical and subcritical flow of multiphase mixtures through chokes. SPE Drill. Complet. 8 (Number 4), 271–276.
Petukov, A., Saputelli, L., Hermann, J., Traxler, A., Boles, K., Nnaji, O., Vrielynck, B., Venugopal, D., 2011. Virtual metering system application in the Ceiba field offshore Equatorial Guinea. In: Paper SPE 144197 Presented at the SPE Digital Energy Conference and Exhibition Held in the Woodland. Texas, USA, 19 – 21 April 2011.
Pilehvari, A.A., 1981. Experimental Study of Critical Two-phase Flow through Wellhead Chokes. OK, University of Tulsa Fluid Flow Projects Report, Tulsa (June 1981).
Poettmann, F.H., Beck, R.L., 1963. New charts developed to predict gas – liquid flow through chokes. World Oil 95, 101.
Rashid, S., Ghamartale, A., Abbasi, J., Darvish, H., Tatar, A., 2019. Prediction of critical multiphase flow through chokes by using A rigorous artificial neural network method. Flow Meas. Instrum. 69, 101579, 2019.
Rastoin, S., Schmidt, Z., Doty, D.R., 1997. A review of multiphase flow through chokes. J. Energy Resour. Technol. 119, 1–10.
Roberts, A.P., Allen, T.O., 1993. Well Compilations, Work over, and Stimulation, fourth ed., vol. 1. OGCI and PetroSkills Publications, Tulsa, Oklahoma, pp. 20–27. Production Operations.
Ros, N.C.J., 1960. An analysis of critical simultaneous gas/liquid flow through a restriction and its application to flow metering. Applied Science Research 9, 374–388.
Rostami, A., Ebadi, H., 2017. Toward gene expression programming for accurate prognostication of the critical oil flow rate through the choke: correlation development. Asia Pac. J. Chem. Eng. 12, 884–893.
Rostami, A., Arabloo, M., Ebadi, H., 2017. Genetic programming (GP) approach for prediction of supercritical CO_2 thermal conductivity. Chem. Eng. Res. Des.2017 122, 164–175.
Sachdeva, A., Schmidt, Z., Brill, J.P., Blais, A.M., 1986. Two-phase flow through chokes. In: Paper SPE15657 Presented at the 61st Annual Technical Conference and Exhibition of the Society of Petroleum Engineers Held in New Orleans. LA October 5-8, 1986.
Sadiq, D.J., 2012. Prediction of oil flow rate through choke at critical flow for Iraqi oil wells. Journal of Petroleum Research and Studies 212 (Number 1), 53–79.
Samanta, B., Al-Balushi, K.R., Al-Araimi, S.A., 2003. Artificial neural networks and support vector machine with genetic algorithm for bearing fault detection. Eng. Appl. Artif. Intell. 16, 657–665.
Scheers, L., Voon, O., Boers, T., 2009. Metering Atlas: a portal to create transparency in production and fiscal measurement data. In: North Sea Flow Measurement Workshop 20-22 October 2009, pp. 1–13.
Scheinost, D., Noble, S., Horien, C., Greene, A.S., Lake, E.M.R., Salehi, M., Gao, S., Shen, X., O'Connor, D., Barron, D.S., Yip, S.W., Rosenberg, M.D., Constable, R.T., 2019. Ten simple rules for predictive modelling of individual differences in neuroimaging. Neuroimage 193 (2019), 35–45.
Schuller, R.B., Munaweera, S., Selmer-Olsen, S., Solbakken, T., 2006. Critical and subcritical oil/gas/water mass flow rate experiments and predictions for chokes. SPE Prod. Oper. 21 (3), 372–380.
Seidi, S., Sayahi, T., 2015. A new correlation for prediction of sub-critical two-phase flow pressure drop through large-sized wellhead chokes. J. Nat. Gas Sci. Eng. 26, 264–278.
Shaban, H., Tavoularis, S., 2014. Measurement of gas and liquid flow rates in two-phase pipe flows by the application of machine learning techniques to differential pressure signals. Int. J. Multiphas. Flow 67, 106–117. https://doi.org/10.1016/j.ijmultiphaseflow.2014.08.012.
Shao, H., Jiang, L., Liu, L., Zhao, Q., 2018. Modeling of multiphaseflow through chokes. Flow Meas. Instrum. 60, 44–50.
Sheppard, C.P., Russell, D., 1993. The application of artificial neural networks to non-intrusive multi-phase metering. Control Eng. Pract. 1 (2), 299–304.

Simpson, H., Rooney, D., Grattan, E., 1983. Two phase flow through gate valves and orifice plates. In: Presented at the International Conference on the Physical Modelling of Multiphase Flow. Coventry, England, 19 – 21 April.
Spiess, A.N., Neumeyer, N., 2010. An evaluation of R^2 as an inadequate measure for nonlinear models in pharmacological and biochemical research: a Monte Carlo approach. BMC Pharmacol. 10 (6), 1–11. http://www.biomedcentral.com/1471-2210/10/6.
Sun, J., Ma, X., Kazi, M., 2018. Comparison of decline curve analysis DCA with recursive neural networks RNN for production forecast of multiple wells. In: Paper SPE – 190104 – MS Presented at the SPE Western Regional Meeting Held in Garden Grove. California, USA, 22 – 27 April 2018.
Surbey, D.W., Kelkar, B.G., Brill, J.P., 1989. Study of multiphase critical flow through wellhead chokes. SPE Prod. Eng. 4 (2), 142–146. https://doi.org/10.2118/15140-PA.
Thorn, R., Johansen, G.A., Hjertaker, B.T., 2013. Three-phase flow measurement in the petroleum industry. Meas. Sci. Technol. 24, 1–17, 012003.
Tsakonas, A., Dounias, G., 2002. Hybrid computational intelligence schemes in complex domains: an extended review. In: Proceedings of the Second Hellenic Conference on AI: Methods and Applications of Artificial Intelligence, ACM Digital Library. Springer, London, pp. 494–512.
Uzel, O., Koc, E., 2012. Basic of Genetic Programming. Graduation Project I, pp. 1–25. Available: http://mcs.cankaya.edu.tr/proje/2012/guz/omer_erdem/Rapor.pdf. (Accessed 14 April 2021).
Vapnik, V., 1995. The Nature of Statistical Learning Theory. Springer, New York.
Wallach, D., 2006. Evaluating crop models. In: Wallach, D., et al. (Eds.), Working with Dynamic Crop Models: Evaluations, Analysis, Parameterization, and Applications. Elsevier, Amsterdam, pp. 11–53.
Wang, L., Liu, J., Yan, Y., Wang, X., Wang, T., 2017. Gas–liquid two-phase flow measurement using coriolis flowmeters incorporating artificial neural network, support vector machine, and genetic programming algorithms. IEEE Transactions on instrumentation and measurement 66 (5), 852–868.
Williams, J., 1994. Status of multiphase flow measurement research. In: Paper SPE 28515 Presented at the SPE 69th Annual Technical Conference and Exhibition Held in New Orleans, LA. U.S.A., 25-28 September 1994.
Woodroof, N., 2020. Why Traditional Methods of Validating Multiphase Flow Meters Are Not Delivering – Part One. Oilfield Technology. https://www.oilfieldtechnology.com/special-reports/22012020/why-traditional-methods-of-validating-multiphase-flow-meters-are-not-delivering-part-one/. (Accessed 14 July 2020).
Xu, L., Zhou, W., Li, X., Tang, S., 2011. Wet gas metering using a revised venturi meter and soft-computing approximation techniques. IEEE Transactions on instrumentation and measurement 60 (3), 947–956.
Xu, Z., Wu, F., Yang, X., Li, Y., 2020. Measurement of gas-oil two-phase flow patterns by using CNN algorithm based on dual ECT sensors with venturi tube. Sensors 2020 20 (1200), 1–18.
Yadav, R.S., Singh, V.P., 2011. Modelling academic performance evaluation using soft computing techniques; A fuzzy logic approach. Int. J. Comput. Sci. Eng. 3 (Number 2), 676–686.
Yan, Y., Wang, L., Wang, T., Wang, X., Hu, Y., Duan, Q., 2018. Application of soft computing techniques to multiphase flow measurement: a review. Flow Meas. Instrum. 60, 30–43.
Zadeh, L.A., 2009. Toward extended fuzzy logic—a first step. Fuzzy Set Syst. 160 (21), 3175–3181. https://doi.org/10.1016/j.fss.2009.04.009.
Zangl, G., Hermann, R., Schweiger, C., 2014. Comparison of methods for stochastic multiphase flow rate estimation. In: Paper SPE 170866 MS Presented at the SPE Annual Technical Conference and Exhibition Held in Amsterdam. The Netherlands, 27 – 29 October 2014.
Zareiforoush, A., Hosseinbagheri, A., Mehrabi, H., 2015. Comprehensive study on surface flow rates/velocities determination in gas condensate producing well through chokes and flexible pipes. In: Paper Presented at the 1st National Conference on Oil and Gas Fields Development (OGFD). Sharif University of Technology. Tehran, Iran, 28-29 January, 2015.
ZareNezhad, B., Aminian, A., 2011. An artificial neural network model for design of wellhead chokes in gas condensate production fields. Petrol. Sci. Technol. 29 (6), 579–587. https://doi.org/10.1080/10916460903551065.
Zhibin, W., Yingchuan, L., Haiquan, Z., Ximao, L., Yonghui, L., 2011. A simple numerical model for the prediction of multiphase mass flow rate through chokes. Petrol. Sci. Technol. 29 (24), 2545–2553. https://doi.org/10.1080/10916466.2011.594829.
Zhou, T., 2017. A Comprehensive Study of Modelling Multiphase Flow through Chokes. Masters degree thesis submitted to the Graduate and Professional Studies of Texas A&M University.
Zhou, T., Kabir, C.S., Hoadley, S.F., Hasan, A.R., 2018. Probing rate estimation methods for multiphase flow through surface chokes. J. Petrol. Sci. Eng. 169, 230–240.