Expert Systems With Applications 93 (2018) 72–85

Contents lists available at ScienceDirect

Expert Systems With Applications

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

Virtual multiphase flow metering using diverse neural network ensemble and adaptive simulated annealing

Tareq Aziz AL-Qutami[a,*], Rosdiazli Ibrahim[a], Idris Ismail[a], Mohd Azmin Ishak[b]

[a] Department of Electrical & Electronic Engineering, Universiti Teknologi PETRONAS, 32610 Seri Iskandar, Perak, Malaysia
[b] Head of Subsea Control, Project Delivery & Technology, PETRONAS, Malaysia

ARTICLE INFO

Article history:
Received 7 March 2017
Revised 4 October 2017
Accepted 5 October 2017
Available online 6 October 2017

Keywords:
Neural network
Ensemble method
Simulated annealing
Multiphase flow
Virtual flow meter
Soft sensor

ABSTRACT

Real-time production monitoring in oil and gas industry has become very significant particularly as fields become economically marginal and reservoirs deplete. Virtual flow meters (VFMs) are intelligent systems that infer multiphase flow rates from ancillary measurements and are attractive and cost-effective solutions to meet monitoring demands, reduce operational costs, and improve oil recovery efficiency. Current VFMs are very challenging to develop and very expensive to maintain, most of which were developed for wells with dedicated physical meters where there exists an abundance of well test data. This study proposes a VFM system based on ensemble learning for fields with common metering infrastructure where data generated is very limited. The proposed method generates diverse neural network (NN) learners by manipulating training data, NN architecture and learning trajectory. Adaptive simulated annealing optimization is proposed to select the best subset of learners and the optimal combining strategy. The proposed method was evaluated using actual well test data and managed to achieve a remarkable performance with average errors of 4.7% and 2.4% for liquid and gas flow rates respectively. The accuracy of the developed VFM was also analyzed using cumulative deviation plot where the predictions are within a maximum deviation of ±15%. Furthermore, the proposed ensemble method was compared to standard bagging and stacking and remarkable improvements have been observed in both accuracy and ensemble size. The proposed VFM is expected to be easier to develop and maintain than model-driven VFMs since only well test samples are required to tune the model. It is hoped that the developed VFM can augment and backup physical meters, improve data reconciliation, and assist in reservoir management and flow assurance ultimately leading to a more efficient oil recovery and less operating and maintenance costs.

1. Introduction

Multiphase flow is a simultaneous stream of more than one component with different physical and chemical properties such as gas, liquid, and solid (MPMS, 2013).A two-phase flow of gas and liquid is very common in oil and gas production fields, and measuring individual flow rates is essential for well surveillance, flow assurance, reservoir management, and production monitoring and optimization (Thorn, Johansen, & Hjertaker, 2012). It is even more significant as fields become economically marginal (Falcone, Hewitt, & Alimonti, 2009). Current practice to measure multiphase flow rates is using multiphase flow meters (MPFMs). MPFMs combine several measurement principles such as Gama ray spectroscopy, capacitance tomography, microwave, and ultrasound to infer phase flow rates (Falcone et al., 2009; Thorn et al., 2012).

However, MPFMs are still economically infeasible to be installed for individual wells and suffer hardware failure particularly in subsea applications (Thorn et al., 2012; Varyan, Haug, Fonnes et al., 2015). In addition, MPFMs suffer high uncertainty and error propagation which necessitates frequent costly calibration (Gryzlov, 2011; MPMS, 2013). This calibration is usually challenging and sometimes impossible in long tie-back subsea networks.

Furthermore, many production fields are still using common metering and flow assurance facilities that rotate and sample production wells one at a time periodically using either a test separator or an MPFM. This monitoring technique is inadequate particularly when wells are mature, rapid changes in water cut (WC) and gas volume fraction (GVF), resulting in late correction actions.

Those limitations triggered the development of virtual flow meter (VFM), a software-based computational model that estimates real-time multiphase flow rates by exploiting existing measurements. It potentially combines cheap hardware with acceptable

* Corresponding Author.
E-mail addresses: tareqaziz2010@gmail.com, tareq.aziz_g03509@utp.edu.my (T.A. AL-Qutami), rosdiazli@utp.com.my (R. Ibrahim), idrisim@utp.com.my (I. Ismail), azminishak@petronas.com.my (M.A. Ishak).

https://doi.org/10.1016/j.eswa.2017.10.014
0957-4174/

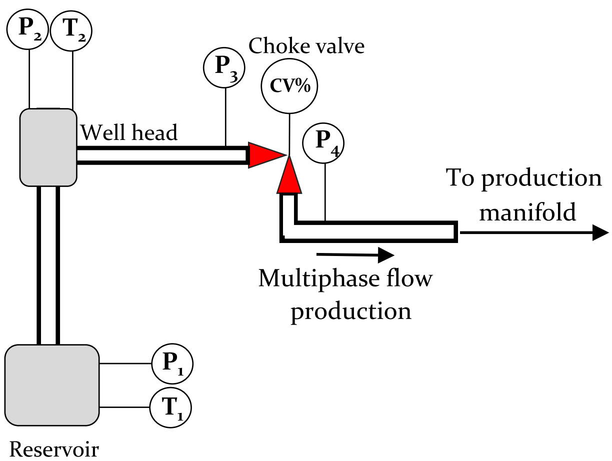

Fig. 1. Typical instrumentation available in a production Well.

Table 1
Summary of related work for data-driven VFMs.

Method	Remarks	Paper
LR	- Only 5 well tests are used to develop the model.	(Zangl et al., 2014)
PCR	- Requires GOR, Oil-water ratio (OWR) and API gravity as inputs.	(Bello et al., 2014)
SVM	- Uses extended Venutri (extra hardware). - Lab-scale with ≈ 10% error.	(Xu et al., 2011)
Fuzzy Logic	- Uses single point P&T as inputs (under-determined system).	(Ahmadi et al., 2013)
PCA+ NN	- Uses DP signals as inputs from Lab-scale vertical pipe. - High prediction error, ≈ 20%.	(Shaban & Tavoularis, 2014)
NN	- NN structure manually selected.	(Ahmadi et al., 2013; AL-Qutami et al., 2017; Berneti & Shahbazian, 2011; Hasanvand & Berneti, 2015; Zangl et al., 2014)

performance and can be easily implemented on existing hardware platforms with minimum additional costs (Bailey, Shirzadi, Ziegel et al., 2013; Falcone et al., 2009). VFM can augment MPFM to reduce measurement uncertainty, act as a backup when MPFM is faulty (redundancy), and provide data reconciliation and increased reliability (Amin et al., 2015; Babelli, 2002). This ultimately improves reservoir recovery and reduces capital and operational expenditures (CAPEX and OPEX) (Amin et al., 2015; Varyan et al., 2016).

Typical instrumentation of an oil and gas production well is illustrated in Fig. 1. It consists of downhole pressure and temperature measurements (P_1&T_1), wellhead pressure and temperature measurements (P_2&T_2), choke valve opening percentage ($CV\%$), and pressure measurements upstream and downstream of the choke valve (P_3&P_4). These parameters are correlated to overall production rate and pressure losses across the flow-line, hence they can be used to infer flow rates and are deemed suitable inputs to VFM systems.

Traditional VFM approaches are based on empirical correlations and mechanistic modeling. Empirical correlations are extracted from experimental data, such as empirical Choke models (Moghaddasi, Lotfi, & Moghaddasi, 2015) that has the following generic formula:

$$Q = \frac{PS^n}{cR^m} \tag{1}$$

where P is the upstream pressure, Q is the production rate, R is the gas-liquid ratio (GOR), S is the choke size, c, m, and n are empirical constants. However, these correlations require GOR which itself is difficult to measure. GOR is usually obtained from lab sampling, hence such correlations would assume constant GOR until next lab results. Moreover, these correlations are limited to certain operational conditions and fluid properties.

On the other hand, the mechanistic (model-based) approach is based on the physical phenomena and multiphase flow dynamics. It highly relies on fluid types and production regimes and is sensitive to changing operating conditions such as GOR and WC (Amin et al., 2015). Deploying and maintaining mechanistic VFMs is very challenging and costly since many parameters are required such as well profile, heat transfer, pipe roughness, productivity index (PI), and fluid composition (Haldipur, Metcalf et al., 2008; Varyan et al., 2016). Furthermore, many mechanistic models are computationally expensive due to the use of multivariate nonlinear solvers to find unique solutions (Bello, Ade-Jacob, Yuan et al., 2014; Haldipur et al., 2008; Varyan et al., 2015).

Since the objective of VFMs is to utilize current knowledge from ancillary measurements to infer multiphase flow rates, intelligent systems using soft computing techniques seem potential candidates to achieve this objective. Such data-driven expert systems are easier to develop and maintain than mechanistic models since they don't require an in-depth knowledge of the underlying physics to infer flow rates (Falcone et al., 2009; Stone et al., 2007). A VFM expert system would be able to establish this inference from the data patterns which is the focus of this article, data-driven VFM systems. Such VFM system can be deployed by adding several computing unit to the field IOT infrastructure. These compute units would retrieve measurements from sensors and relay the flow rate estimations to the supervisory control and data acquisition system.

Several data-driven techniques have been proposed to develop VFM systems such as least squares linear regression (LR) to estimate water and liquid flow rates (Zangl, Hermann, Schweiger et al., 2014), principal component regression (PCR) to estimate oil and gas flow rates in offshore wells (Bello et al., 2014), support vector machine (SVM) combined with venturi meter (Xu, Zhou, Li, & Tang, 2011), and the most popular technique is neural networks (NN) (Ahmadi, Ebadi, Shokrollahi, & Majidi, 2013; AL-Qutami, Ibrahim, Ismail, & Ishak, 2017; Berneti & Shahbazian, 2011; Hasanvand & Berneti, 2015; Zangl et al., 2014). A summary of these studies is presented in Table 1.

Some of these studies used experimental setups to collect data (Shaban & Tavoularis, 2014; Xu et al., 2011) or used data representing a short production period, three months (Hasanvand & Berneti, 2015) and thirty hours (Zangl et al., 2014), to develop VFM models. These studies may not capture complex multiphase behaviors or represent production trends accurately, especially in new wells where production is kept almost constant. Moreover, some studies only focused on predicting one component flow rate (oil) in the multiphase flow and used temperature and pressure measurements at one or more points along the flow-line without accounting for choke opening (Ahmadi et al., 2013; Berneti & Shahbazian, 2011; Hasanvand & Berneti, 2015). This may limit the long-run performance of VFM and may impose frequent calibrations due to reservoir and production changes over time particularly when downhole pressure is not taken into account. Besides, considering P&T at a single point only results in under-determined and very sensitive system (Ahmadi et al., 2013; Hasanvand & Berneti, 2015).

Aside from aforementioned limitations, current VFMs in literature are developed using data collected from dedicated meters.