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Improved Gas-liquid Flow Meter Using a Neural Network

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Summary:
This paper presents an improved gas-liquid flow rate meter based on gas fraction, pressure drop measurements, and an Artificial Neural Network (ANN). The available database comprises 416 sets of data, in which 50% is applied to train, 10% to validate and 40% to test the ANN. We evaluated the performance of the network considering 10 neurons at the hidden layer. Quantitative results are presented, regarding gas and liquid flow rate estimation, showing significant improvements compared to a previous methodology based on algebraic approximations.

Keywords: gas-liquid flow, flow rate measurement, gas fraction, pressure drop, artificial neural network

Introduction

The knowledge of parameters such as phase fractions and phase flow rates is necessary for control and optimization strategies in petroleum production and processing. Multiphase inline flow meters (MPFM) have been proposed to measure the flow rate of individual phases (e.g. gas and oil) by applying several technologies, among others for instance through arranging different sensors in the pipeline and applying correlation models to obtain the desired parameters. Artificial Neural Networks (ANN) are used in a variety of problems occurring either in research or in the industry [1]. Here, we describe the application of an ANN to reduce the uncertainty of a previously presented MPFM, as a first step towards an intelligent calibration routine since only a few parameters are required to train the neural network.

Gas-liquid Flow Rate Meter

In our earlier work, a gas-liquid flow rate meter [2] was introduced with the purpose of being simple and having no dependency on reference measurements or on calibration procedures as is usual for other solutions. Hence, the flow rate meter considers simple and direct algebraic approximations (AA) to compute gas and liquid superficial velocities (J_G and J_L) based on capacitance readings of the twin sensor, pressure drop fluctuations through a Venturi tube and, pressure and temperature information, as summarized in Fig. 1. For details on implementation and results, please refer to [2].

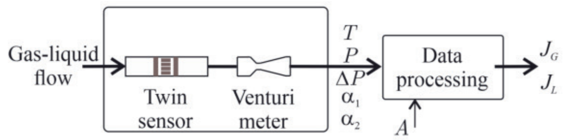

Fig. 1. Schematic illustration of the gas-liquid flow meter [2].

We chose the superficial velocity *J* as the target parameter because it is a more usual and general parameter than flow rate, considering that it is independent of the pipe diameter, as *J* is the ratio of the phase volumetric flow rate to the pipe cross-section area.

Experimental Database

The gas-liquid flow meter proposed in [2] was tested in a horizontal test bench located at NUEM/UTFPR, Brazil. A total of 416 experimental points were measured during 60 seconds in a 1-inch pipe inner diameter. Most of the experimental points developed slug flow regimes. The database comprises average parameters of the acquisition interval such: the cross-sectional gas fraction α of the capacitive sensor; the gas mean velocity v_G; the pressure fluctuations ΔP through a Venturi tube; pressure and temperature information of the two-phase mixture and, reference values of gas and liquid flow rate.

Artificial Neural Network

In this work, we apply an ANN in the data processing step, represented in Fig. 1, to accomplish the computation of the gas and liquid flow rate. The ANN reproduces the Levenberg Marquardt algorithm with backpropagation to propagate errors from the output layer back to the input layer by a chain rule. This process performs adjustments of its synaptic weights and bias levels in the learning process through an iterative process. The ANN configuration, represented in Fig. 2 has (i) 2 inputs: phase fraction readings and pressure fluctuations ΔP (ii) 10 neurons at hidden layer and (iii) 2 outputs, as gas and liquid flow rates. The mapping between input parameters and target data is performed throughout layers of neurons with a non-linear sigmoid activation function. As a common practice in neural networks, we divided the database into training, validation and test datasets. Since the targets are a function of only two parameters, it seems not to be a complex task to fit the model. Thus, we use only 50% of the database for training, keeping in mind that the selected data have to cover the full range of targets. With the hypothesis that the model will have few hyperparameters and, consequently it will be easy to validate and tune it, we can reduce the size of the validation dataset and have a good amount of data for testing and comparison with our results presented in [2]. Therefore, we split the rest of the database into 10% for validation and 40% for testing.

Results

The performance of the proposed ANN is analyzed based on the root mean-squared deviation (RMSD) of the output values relative to the target parameters. The results are an RMSD for training, validation and testing data of 0.0508, 0.0555 and 0.0463 m/s, respectively. In Fig. 3 we show the results for testing data - 166 operating points. Dotted lines represent a deviation of 10%. We also compare the same operating points with the AA result from our previous work [2]. As one can notice, the flow rate estimation was clearly improved by the proposed methodology, mainly for the lower range of liquid superficial velocity and for the higher range of gas superficial velocity. Quantitatively, the percent RMSD decreased from 16.2% to 8.6% for gas and from 18.1% to 5.4% for liquid flow rate.

Conclusions

In this work, we introduced an ANN-based method applied in a gas-liquid flow rate meter. The gas and liquid superficial velocities are mapped using only two measured parameters, the gas fraction and pressure drop through a Venturi tube. Ten neurons at the hidden layer, two at the output layer and 50% of the experimental basis were sufficient to achieve improvements in the gas and liquid flow rate estimation. Representing 7.6% and 12.7% of reducing in the RMSD%, for gas and liquid respectively. As a next step of the work, we aim to expand the proposed methodology to a larger database, in which fluid properties significantly change over the experimental points.

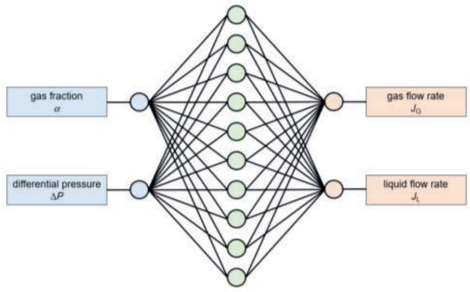

Fig. 2. Representation of the designed ANN to obtain gas and liquid flow rates.

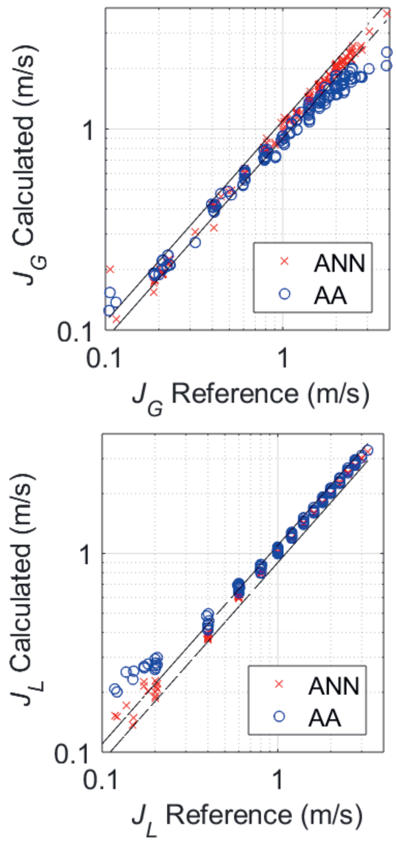

Fig. 3. Improved results of gas and liquid flow rate estimation based on the ANN model.

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