International Journal of Multiphase Flow 67 (2014) 106–117

Contents lists available at ScienceDirect

International Journal of Multiphase Flow

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

Measurement of gas and liquid flow rates in two-phase pipe flows by the application of machine learning techniques to differential pressure signals

H. Shaban, S. Tavoularis *

Department of Mechanical Engineering, University of Ottawa, 161 Louis Pasteur, Ottawa, ON K1N 6N5, Canada

ARTICLE INFO

Article history:
Received 26 May 2014
Received in revised form 25 August 2014
Accepted 27 August 2014
Available online 6 September 2014

Keywords:
Two-phase
Flow rates
Differential pressure
Independent Component Analysis
Principal Component Analysis
Neural networks

ABSTRACT

A new method for the determination of gas and liquid flow rates in vertical upward gas–liquid pipe flows has been proposed. This method consists of an application of machine learning techniques on the probability density function (PDF) and the power spectral density (PSD) of the normalized output of a differential pressure transducer connected to two axially separated wall pressure taps in the pipe. The two-phase flow regime was first identified by the application of the elastic maps method on the differential pressure PDF. The transducer signal was then pre-processed using Principal Component Analysis, and independent features were extracted using Independent Component Analysis. The extracted features were used as inputs to multi-layer back-propagation neural networks, which gave the phase flow rates as output. The present method was used to calibrate a differential pressure sensor to estimate the flow rates of both phases in air–water flow in a vertical pipe of diameter 32.5 mm and in the pressure range from 100 to 140 kPa. Predictions of the present method were in good agreement with direct flow rate measurements. Compared to previously used methods of feature extraction from differential pressure signals, the present method was the only one to have a good, consistent performance over all flow regimes and for all flow conditions encountered in this study.

Introduction

The present research was motivated by the need to measure simultaneously and economically the liquid flow rates in a large number of pipes containing air–water mixtures. This situation arises in laboratory models of nuclear reactor header-feeder systems under conditions simulating hypothetical nuclear accidents, such as loss-of-coolant accidents. In these cases, the feeder tubes would supply emergency coolant to the fuel channels of the reactor core and it is paramount that each feeder provides sufficient liquid flow to adequately cool the corresponding fuel channel.

A thorough review of multiphase flow rate measurement methods was presented by Falcone et al. (2002) and Thorn et al. (2013). A classical method of measuring the gas–liquid flow rates is the separation of the flow into gas and liquid streams and then measuring the flow rate of each stream using single phase flow meters. This method is accurate and reliable, but it is also highly intrusive and requires the use of expensive and bulky separators.

Methods that do not require phase separation, commonly referred to as Multiphase Flow Meters (MFMs), have also been developed. Ideally, MFMs would measure the void fraction and both phase velocities directly. Numerous options exist for relatively accurate measurements of void fraction, however, direct measurement of either phase velocity is very hard for practical reasons. The cross-correlation method is a common indirect approach for estimating the interfacial velocity from the average time of flight of the gas–liquid interfaces between two axially spaced signal detectors (for example, Dong et al. (2005) and Tan and Dong (2006)). This method can only be used when there is a clearly defined interface normal to the streamwise direction, as in bubbly and slug flows, so it would not be suitable for annular flows, for example; moreover, the relationship between the interfacial velocity calculated using the cross-correlation method and the velocity of either phase may be unknown or even non-unique under some flow conditions (Falcone et al., 2002). For example, calculation of the gas flow rate by integrating the product of void fraction and gas velocity requires knowledge of the temporal and spatial distribution of these properties. The cross-correlation method cannot provide a time history of gas velocity, because its output is a single-valued estimate of the average interfacial velocity, under the

* Corresponding author. Tel.: +1 613 562 5800x6271; fax: +1 613 562 5177.
E-mail addresses: hshab073@uottawa.ca (H. Shaban), stavros.tavoularis@uottawa.ca (S. Tavoularis).

http://dx.doi.org/10.1016/j.ijmultiphaseflow.2014.08.012
0301-9322/

assumption that the temporal fluctuations of gas velocity would be negligible. We have discussed this issue in detail in a separate manuscript (Shaban and Tavoularis, 2014b), in which we proved that neglecting the temporal or spatial fluctuations of the gas velocity would introduce errors in the predictions of gas flow rate, especially at relatively large gas and liquid flow rates. A main conclusion of that work is that the cross-correlation method is capable of estimating fairly accurate the phase flow rates only within very narrow ranges of flow conditions.

Some MFMs are based on differential pressure measurement across obstructions, including Venturi tubes (for example, Meng et al. (2010)) and orifice plates (for example, Lin (1982) and Zhang et al. (1992)), along with estimates of mass quality at the measurement location. Venturi tubes and orifice plates can be calibrated to measure the mass flow rate of the two-phase mixture from the pressure drop across the device. Empirical correlations are typically used to obtain the mass quality of the flow from the void fraction, measured using a void fraction meter. The mass flow rate of each phase can then be calculated separately by using the mixture mass flow rate and the mass quality. It is required, when using these devices, for the flow to be homogenized upstream of the measurement device to avoid dependence of the results on the flow regime and to ensure reproducibility. Another general limitation of these methods is that they rely on empirical models and so become specific to a particular flow set-up, in which they need to be calibrated.

Another type of MFMs is based on the application of machine learning regression techniques, such as neural networks or support vector regression, on some features of a measured parameter (pressure, conductivity and radiation attenuation, among others), whose fluctuations correspond to fluctuations in the phase composition of the flow. For example, Beg and Toral (1993) presented a method based on pattern recognition of features derived from the time histories of differential and absolute pressure signals across an orifice plate in horizontal air–water pipe flow with a homogenizing device. Cai and Toral (1993) expanded on this study and used first a Kohonen self-organizing map to classify the flows into different regimes and then neural networks to estimate the gas and liquid flow rates. Minemura et al. (1998) used a correlative mapping method to calculate the phase flow rates from stochastic features derived from the differential pressure signal across a Venturi tube, preceded by an eccentric elbow, which homogenized the flow. In another study, Meribout et al. (2010) used neural networks along with features extracted from the signals of five different types of sensors (including acoustic, impedance and pressure signals) to estimate the phase flow rates with a 5% uncertainty. Most recently, Fan and Yan (2013) used neural networks to estimate the gas and liquid flow rates for measurements in the slug flow regime, from mechanistic features extracted from the conductance signals of two probes. MFMs of this type also need to be calibrated before use, but they may potentially utilize, as an input, any flow property that varies with phase composition, thus introducing the possibility of a non-intrusive measurement. When the flow property, that is used as an input, can be measured by relatively inexpensive means, such methods can be quite economical.

The present study is aimed at developing an accurate two-phase flow metering method that would be suitable for simultaneous and cost-effective flow rate measurements in vertical upward gas–liquid flows in a large number of pipes. Such a method should, ideally, be free of complicated or expensive instrumentation and be non-intrusive. It should operate effectively in all flow regimes, without prior knowledge of the regime or the need for homogenizers. Previous experimental studies in facilities with large numbers of pipes have been performed by either limiting the number of pipes in which measurements were collected (Kowalski and Hanna, 1989) or by utilizing a single set of instruments for successive measurements in all of the pipes (Teclemariam et al., 2003), which required an excessive amount of time for measurements at each set of flow conditions. Following evaluation of various options, we chose the following approach: (a) differential pressure transducers connected to taps in a straight pipe were used as sensing devices; (b) Principal Component Analysis and Independent Component Analysis were used to extract independent features from the differential pressure signals; and (c) neural networks models were used to correlate these features to the gas and liquid flow rates. The flow regime was identified from the same differential pressure signals by the use of the method of elastic maps, which has been developed by Shaban and Tavoularis (2014a); for brevity, this article will be henceforth referred to as ST1. The present method of flow regime identification may also be applied to signals provided by other instruments, such as impedance void meters (Mi et al., 1998), electrical capacitance tomographs (Jeanmeure et al., 2002) and conductivity probes (Julia et al., 2008). In the following sections, the data analysis and machine-learning techniques that were used in this study will be briefly introduced, then the proposed method will be outlined and, finally, some representative results of the present analysis will be presented and compared to those obtained with the use of approaches introduced by previous authors.

Background

Terminology

Standard terminology, as established in machine-learning analysis, will be used in the following sections; some of these terms will be defined here for clarity. A *dataset* is a collection of data points, called *examples*, each of which can be represented as a vector of several values, called *features*. The number of features is called the *dimension* of the dataset. For instance, in the present study, the input dataset comprises differential pressure measurements, each of which is an input example composed of 12,000 input features, which are discrete values recorded at a rate of 200 samples/s over a time interval of 60 s; therefore, this dataset has a dimension equal to 12,000. Machine learning algorithms can be used for *classification*, which is a process providing, as output, a class selected among a set of classes. They can also be used for *regression*, which is a process providing, as output, a real number. An algorithm is first used to *train* a model on a certain portion of the entire dataset, called the *training set*. The objective of the training process is to calculate the unknown coefficients/weights in the model. The process of determining the optimal values of the user-specified parameters in the models is called *validation*. Finally, the trained algorithm is tested against a *test set*, which was not used for the calculation of the model coefficients or the selection of the model parameters. A trained algorithm that performs equally well on both the training and the test datasets is said to have good *generalization* performance. In some cases, a trained algorithm performs very well with the training dataset but very poorly for test examples, even if they are within the calibration (training) range, a situation referred to as *overfitting*.

Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is a signal processing method for representing a measured signal as a linear summation of several independent components (Hyvarinën and Oja, 2000). Besides its use to decompose a signal into additive components, ICA can also be used for feature extraction and dimensionality reduction. In this study, ICA will be used to reduce the dimension