A method for characterization of the turbulence properties of wet gas flow across a V-cone

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Abstract The paper demonstrates the existence of a relationship between stochastic characteristics of the pressure signal and individual phase compositions and flow rates in “wet gas” flow. Neural networks can be trained on these stochastic characteristics to predict (measure) the flow rates of individual phases (liquid and gas).
Keywords: wet gas, turbulence properties, wet gas metering, multiphase flow metering

1. Introduction

The paper is based on measurements taken at the National Engineering Laboratory (UK) wet gas test loop. The test matrix covered a range of flow conditions up to 15% liquid volume fraction and up to 60 bar. Differential and absolute pressure signals were sampled at high frequency across a V-cone. Turbulence characteristics of the flow captured in the sampled signals were characterized by pattern recognition techniques and related to the fractions and flow rates of liquid and gas phases. The methodology presented has the potential to be developed as an online wet-gas flow measurement system capable of correcting for the overreading on the gas flow rate resulting by liquid loading [1].

2. Equipment, Test Conditions, Method

The systems tested comprised two 6” V-cone meters with beta ratios of 0.55 and 0.75 connected to high frequency absolute and differential pressure gauges and a portable PC as the data acquisition system. The test fluids was kerosene substitute and nitrogen gas. The test matrix comprised gas flow rates at 400, 600, 800 up to1000 m^3/hr at two pressures levels 15 and 60 bar. For each gas and pressure combination, a set of liquid flow rates were passed corresponding to Lockhart-Martinelli parameters of 0, 0.01, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3 and 0.5 (GVF from 100% to 85%). The test matrix was repeated for the two V-cone meters. The test matrix worked out to around 30 test points at each pressure level per V-cone. The test matrix superimposed against the Mandhane multiphase regime map in Fig. 1 below indicates that the flow conditions can be characterized as annular – dispersed flow regime.

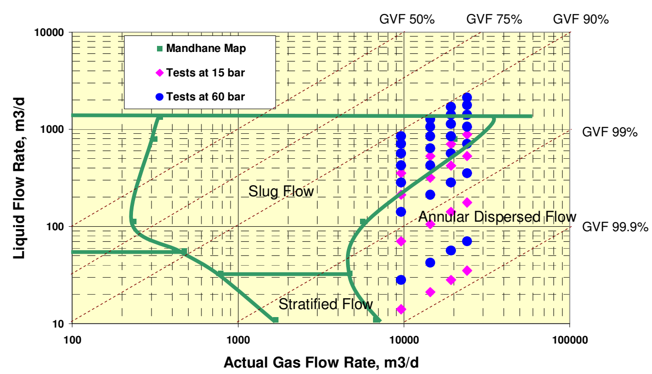

Fig. 1 Test Matrix and Mandhane Flow Regime Map

V-cone differential pressure signals were sampled and analysed by the ESMER methodology (Expert System for Multiphase Metering). [2]. The essence of ESMER is to extract characteristic features from fluctuating differential and pressure signals sampled at high frequencies. The features are then related to the flow rates of individual phases by neural net training. The objective of the present test was to find out whether a VCone meter / ESMER combination could predict the gas and liquid flowrates through the liquid range $0 < X < 0.5$. It was expected that with increasing liquid loading the turbulence characteristics would become more prounounced resulting in smaller uncertainties in liquid and gas flowrate predictions.

In simple mathematical formulation the ESMER methodology can be described as follows:
Flow rates of individual phases =

function (momentum transfer characteristics, fluid properties, pipeline properties) (1)

where,

momentum transfer characteristics =
function (stochastic features derived from high frequency wave forms) (2)

In neural networking terminology, the terms on the left hand side of relationship 1 represent the targets of a supervised network and those on the right hand side represent the training inputs. The wave forms in relation 2 can emanate from any sensor which responds to fluid turbulence.

The features input into the neural nets can take the form of absolute values (e.g. pipeline diameter, inclination to horizontal, salinity, etc), fuzzy values (e.g. flow regime), or stochastic properties derived from time series (e.g. standard deviation of permittivity, etc).

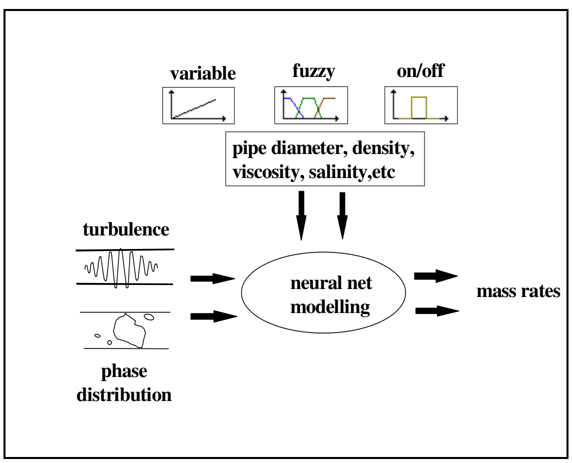

Fig.2 **ESMER Conceptual Model**

In general the neural net system comprises a master net on the first layer and a number of sub-nets in the second layer. The master net triggers different back-propagation nets. The output of these sub-nets is the specific measurement targets such as water cuts, liquid and gas flow rates. The exact system of algorithms and weights which form a given neural net system is derived from calibration runs conducted in a multi-phase laboratory. The calibration matrix should cover a representative cross section of the operating envelope of the target process line. Briefly, during calibration a plurality of stochastic features derived from the ESMER sensor signals are trained with a supervised neural net against a plurality of reference measurements of individual phase flow rates. Thus the calibration of the wet gas flow meter comprises the weights of the neural nets.

3. Results

Results of the tests are now presented for V-cone of beta 0.75. The results for beta 0.55 showed a very similar trend but with a wider scatter. Therefore, the results for beta 0.55 is omitted as they do not have a significant effect on the conclusions of this paper.

3.1 Feature Ranking and Selection

One of the most important steps towards achieving successful flow rate identification is the selection of features capable of efficiently representing the hydrodynamic information in the wet gas flow system. Features extracted from fluctuating pressure and differential pressure signals must exhibit characteristics which permit the neural net to distinguish between neighbouring liquid / gas matrix nodes (ie liquid and gas flow rates) used in the training set.

The distinctiveness of the features can be qualitatively assessed from their contour maps across liquid / gas coordinates. An example set of such maps extracted from the differential pressure signal is shown in Figure 3.

Feature f1 of Figure 3(a), reveals that the contour levels rise diagonally (ie feature responds equally to both gas and liquid flow rates). Feature f4 of Figure 3 (b) exhibits vertical contour lines for gas flow rate less than 640 m^3/hr. Thus f4 is more sensitive to gas variation than to liquid variation. Features f5 and f6 of Figures 3 (c) and (d) exhibit a horizontal orientation where liquid flow rate is less than 20 m^3/hr. Thus these features will be more useful in identifying the liquid flow rate.

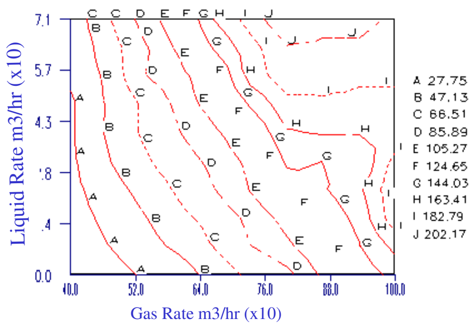

Fig. 3 (a) DP Turbulence Feature f1

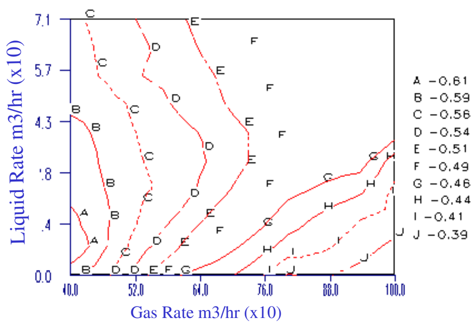

Fig. 3 (b) DP Turbulence Feature f4

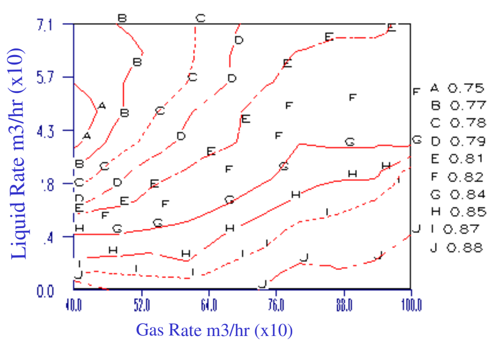

Fig. 3 (c) DP Turbulence Feature f5

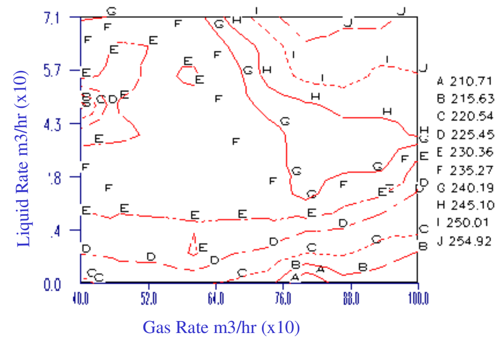

Fig. 3 (d) DP Turbulence Feature f6

Contour maps provide a qualitative assessment of the possibility of turning a feature set into a flow meter capable of identifying flow rates. However, we require a quantitative method for selecting the most efficient features and to discard redundant features for optimum computational efficiency in the neural net. There are a number of methods for ranking the distinctive capability of features extracted from stochastic signals. The Saliency Test is the method preferred in ESMER, although other methods, such as F and D-ratio analysis are also used [2,3,4]. The most efficient feature set selected by the Saliency Method was used to train a back propagating neural net where inputs were the features of the differential pressure signal and outputs were the target engineering measurements (ie liquid and gas rates in this instance).

3.2 Data Set

The total observation period at each flow condition (test matrix point) was four minutes. During this period ESMER took four distinct sample records of 40 seconds duration (there was a short pause between each sample record for computer operations). The sample data set was first analysed by self testing the neural nets where features extracted from all four sample records are used in training the neural net and the same samples are used for testing. The data was then subjected to reproducibility testing where the first two sample records were used for training the neural net and the remainder (one or two records depending on flow conditions) was used for testing.

3.3 Neural Net Self Testing

The neural net models were trained on every available data point and were self tested at 15 bar (33 points) and 60 bar (30 points). The sensitivity of the model to liquid loading (expressed in in terms of the Lockhart – Martinelli parameter – X) is shown in Figures 4 and 5 below. The accuracy of the predictions are summarised in Tables 1 (15 bar) and Table 2 (60 bar) across low liquid (X<0.1) and high liquid (X>0.1) bands. The accuracy of the prediction of the gas flow rate was very good and improved with increasing pressure from RMS 1.51% at 15 bar to 1.11% at 60 bar. The accuracy of the liquid prediction deteriorated with decreasing liquid loading as the liquid rate fell under the resolution of the neural net (determined by the density of points in the training matrix). At the higher liquid loading band (X>0.1), the accuracy of the liquid flow rate prediction improved with increasing pressure from RMS 8.78 % (15 bar) to 5.42% (60 bar). At low liquid loading (X<0.1) the trend was in the opposite direction and the accuracy deteriorated from 22.15% at 15 bar to 41.74% at 60 bar.

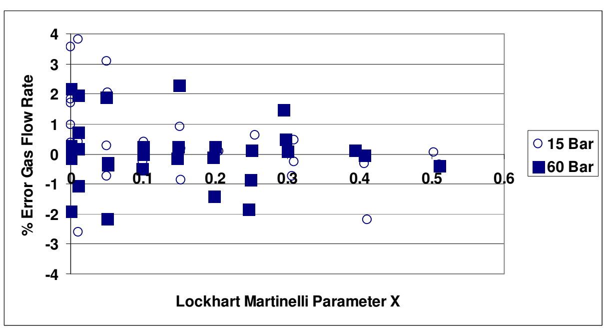

Fig.4 Self testing - gas rate accuracy vs Lockhart Martinelli parameter

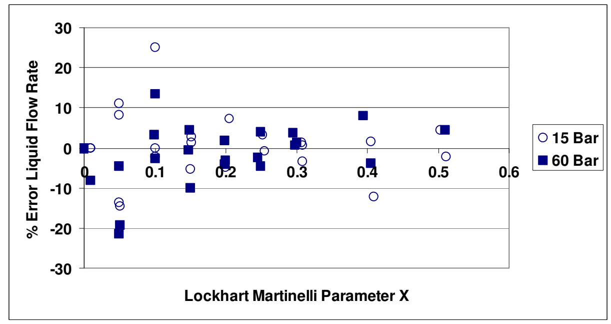

Fig.5 Self testing - liquid rate accuracy vs Lockhart Martinelli parameter

	RMS (%)		
15 bar	All points	Low Liquid X<0.1	High Liquid X>=0.1
Liquid	16.67	22.15	8.78
Gas	1.51	1.86	1.06
Number of Test Points	33	17	16

Table 1 Self testing - summary of results at 15 bar (X of 0.1 corresponds to GVF of 0.986.)

	RMS (%)		
60 bar	All points	Low Liquid X<0.1	High Liquid X>=0.1
Liquid	27.78	41.74	5.42
Gas	1.11	1.32	0.91
Number of Test Points	30	15	15

Table 2 Self testing – summary of results at 60 bar (X of 0.1 corresponds to GVF of 0.973.)

3.4 Reproducibility Test

The study described above was repeated to test the performance of the neural net when tested with measurements not used in the training of the neural nets. For ease of reference we have called this study the Reproducibility Test. The variation of the accuracy of the predictions against Lockhart-Martinelli parameter (X) is shown in Figures 6 and 7. The variation exhibits the expected trend of

increasing accuracy with increasing pressure and X.

The accuracy of the predictions are summarised in Tables 3 (15 bar) and Table 4 (60 bar) across low liquid (X<0.1) and high liquid (X>0.1) bands. The accuracy of the prediction of the gas flow rate was considered to be good and improved slightly with increasing pressure from RMS 1.85% at 15 bar to 1.76% at 60 bar. The accuracy of the liquid prediction deteriorated with decreasing liquid loading as expected. At the higher liquid loading band (X>0.1), the accuracy of the liquid flow rate prediction improved with increasing pressure from RMS 13.57 % (15 bar) to 11.47% (60 bar). At the lower liquid loading band (X<0.1) the liquid flow rate prediction accuracy deteriorated from 30.68% to 42.30%.

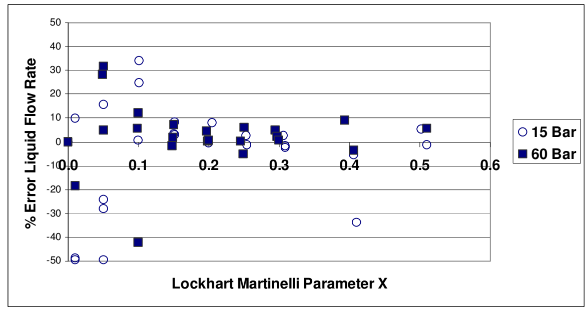

Fig.7 Reproducibility - liquid rate accuracy vs Lockhart Martinelli parameter

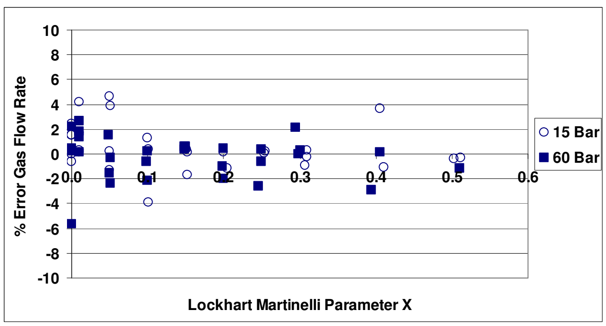

Fig.6 Reproducibility - gas rate accuracy vs Lockhart Martinelli parameter

	RMS (%)		
15 bar	Full range	Low Liquid X<0.1	High Liquid X>=0.1
Liquid	23.48	30.68	13.57
Gas	1.85	2.18	1.47
Number of Test Points	33	17	16

Table 3 Reproducibility – summary of results at 15 bar

	RMS (%)		
60 bar	Full range	Low Liquid X<0.1	High Liquid X>=0.1
Liquid	29.16	42.30	11.47
Gas	1.76	2.16	1.39
Number of Test Points	30	15	15

Table 4 Reproducibility – summary of results at 60 bar

4. Conclusion

The differential pressure signal across a V-cone exhibits characteristic turbulence features which can be related to the flow rates of the liquid and gas phases. The differential pressure must be sampled at a high frequency (above 400 Hz) to bring out such features. The features, comprising stochastic parameters of the signal in amplitude, frequency and time domains, can be ranked in order of significance by means of the Saliency Test. A set of such features can be trained by means of a back propagating neural net against the flow rates of liquid and gas phases. This paper proposes and tests the concept that the neural net trained in this manner can then form the basis of a wet gas flow meter.

In laboratory tests conducted at 15 bar and 60 bar, the accuracy of the gas rate prediction was under 2% RMS across the full range of liquid loadings tested (X=0.01 to 0.5 corresponding to liquid fraction of 0.14% to 7.59%). The liquid rate prediction was highly dependent on the liquid rate and achieved around 12% RMS for liquid loading greater than 3%.

The accuracy / resolution of the neural net depends on the density of the test matrix and the accuracy reported in this paper can be improved by obtaining a larger number of data points. The neural nets can be generalized for different fluids and in-situ effects by training against test matrices obtained at different test loops and field measurements.

Reference

[1] D. Stewart, D. Hodges, R. Steven, RJW Peters Wet Gas Metering with V-cone Meters North Sea Flow Measurement Workshop 22-25 October 2002

[2] T. Darwich, H. Toral and J. Archer, A stochastic study of horizontal two-phase flow, SPE paper 19511, 1989.

[3] S. Cai and H. Toral, Flow rate measurement in air-water horizontal pipeline by neural networks, Proc. Int. Joint Conf. On Neural Networks, 1993, Vol. 2, Nagoya, Japan, 25-29 October, 2013-2016.

[4] H. Toral, S. Cai, E. Akartuna, K. Stothard and A. Jamieson, Field tests of the Esmer multiphase flowmeter, The North Sea Flow Measurement Workshop, 26-29 October 1998, Perthshire, Scotland.