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An Expert System for Multiphase Measurement and Regime Identification

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ABSTRACT

ESMER is a novel PC based package which can measure individual flowrates of gas and liquid phases in multiphase flow by matching the hydrodynamic turbulence characteristics of the flow, represented by pressure and void fraction waveforms, to a calibration database. The method applies advanced random signal processing algorithms employed in voice recognition and seismic analysis. A "calibration feature vector database" is first constructed on the superficial liqud-gas velocity domain. Pattern recognition techniques can then be applied to match the "feature vector of measured samples" to the "calibration database".

ESMER is available as a turnkey multiphase flowrate measurement system consisting of sensor's of user's choice, an analog to digital converter and a personal computer. Existing absolute or differential pressure electronic transducers or a simple void fraction sensor, such as a capacitance sensor could be used. The software is menu driven and includes facilities for digital filtering of noisy signal, graphical presentation of results and the compilation of the rig dependent feature vector calibration database. Help menus are provided.

ESMER has yielded accuracies of $\pm5\%$ in laboratory trials. Its principal advantages are ease of installation and maintenance.

ESMER poses no obstruction to the flow line and would not normally require any modification to the flow line.

INTRODUCTION

No one needs reminding that oil and gas production requires the handling of multiphase fluids. The economy of the production facilities, in particular in offshore installations, is determined to a large extent by the capabilities of the multiphase transportation and metering technology.

At present the multiphase fluid handling capabilities of the petroleum industry rests principally on the design of separators. In other words, in the absence of any true multiphase fluid handling capabilities we have reverse engineered the problem. Multiphase fluids are separated into single phase streams before they can be transported or metered. This is a costly arrangement.

Considerable sums of money have been spent in recent years on research programmes to develop a multiphase meter. However, success is thin on the ground yet. The only multiphase meter which has enjoyed a certain degree of field application to date is the Coriolis mass flowmeter[1]. However, for a multiphase meter, the Coriolis meter has a fundamental weakness. It is too sensitive to gas content and appears to break down at gas ratios above 10%.

This paper presents a novel multiphase metering system which was developed by lateral application of signal analysis and pattern recognition techniques commonly employed in other fields such as speech recognition, seismography and medical electronics. The multiphase meter, ESMER, which was devised during our four year long research and development programme at Imperial College[2], is essentially a software product which converts a desktop PC fitted with an A/D converter to an on-line multiphase meter when connected to turbulence sensors of your choice. For example, ESMER would work satisfactorily with ordinary electronic pressure transducers (differential or absolute); an obvious choice for simplicity, ease of maintenance and nonintrusive measurement.

References and illustrations at end of paper

BACKGROUND

Our research was inspired by advances in speech recognition and speaker identification. The question which came to mind in connection with multiphase flow was: Could there be significant parallels between "human speech" and "fluid sound" ?

Most of us are aware of the fact that fluids flowing in pipelines emit fairly distinctive sound waves in the audio frequency range. Fluid sound depends on a number of factors such as the topology of the flow line, the speed of flow, the physical properties of the fluid, the presence of air traps *etc.*

"Fluid sound" has two components, discrete and broad band frequency. Discrete frequency sound is emitted indirectly by excitation of the pipe (or other material in the path of the fluid) and broadband frequency (noise) is emitted directly by the turbulent fluid motion.

Thus, in a broad sense the human voice can also be viewed as "fluid sound" and we might be permitted to draw an analogy between human speakers emitting distinctive voice spectra and multiphase flow regimes emitting distinctive sound/noise spectra.

Speech, on the other hand, is produced as result of a complex sequence of transformations occurring at several different levels: semantic, linguistic, articulatory and acoustic. It is true that the paths of speech and fluid sound recognition cross only in the acoustic domain. However, in most speech analysis methods it is assumed that differences in these transformations are likely to be reflected in the acoustics. In any case even semantic and syntactic analysis of speech waveforms, based on "artificial intelligence" methods, appear to present certain parallels with our subject (see below 'contextual analysis').

Infact a vast range of applications of seemingly different nature are now being treated under a single umbrella named, Pattern Recognition Theory. Under this umbrella, speech recognition sits side by side with modern techniques of warfare (e.g. identification of enemy vessels by image processing), medical diagnosis (e.g. electrocardiogram analysis), oil discovery (e.g. seismic analysis), data processing (optical character readers), manufacturing industry (e.g. quality control by infrared image analysis of products). Many other application areas are continually being created through Pattern Recognition Theory. We show here an interesting application to multiphase flow measurement.

ESMER

The flowsheet of ESMER is shown in outline in Figure 1. Like most other recognition techniques, ESMER consists of three fundamental parts:

1. Sensors to provide the signals representing physical properties of the "object" (multiphase flow regime).

2. The Extractor to select from the signals the significant features of the "object".

3. The Categoriser to identify the class to which the "object" belongs.

Sensors

ESMER can be used in conjunction with any sensor which can sense the hydrodynamic properties of the flow with a high frequency response. Differential and absolute pressure gauges are recommended for ease of installation and non-intrusive measurement. We have also tested ESMER with void fraction records obtained from simple conductance and capacitance transducers. Void fraction waveforms (area or local) enhance the accuracy of the meter but they are not essential. Any number of waveforms can be processed by ESMER. In general, accuracy is improved with the range and number of waveforms. For example, several differential pressure gauges can be employed to give multiple waveforms for various axial and radial pressure tapping configurations.

To complete the measurement system, a personal computer with a 12 bit A/D converter is all that is needed. The sampled waveform is kept in memory for the Extractor and/or archived on the hard disk. Optimum sampling frequencies and record lengths do exist and are taken into consideration by ESMER.

The Extractor

Extraction is a three stage operation comprising; filtering and visual display (time and frequency domains), feature extraction and feature archiving. In terms of a more familiar term, the Extractor refers to the set of procedures by which ESMER is calibrated. ESMER requires in-situ calibration. Therefore a secondary measurement standard is required in-situ. This is likely to take the form of a separator equipped with single phase flowmeters.

ESMER provides the user with a menu driven utility to design and implement digital filters to suit the particular requirements of the installation. Both recursive and non-recursive filters of lowpass, highpass, notch and bandbass types can be designed by the novice user to exclude the particular noise frequencies affecting the measurement. The gain characteristics of the filter and its effect on the signal can be displayed in both frequency and time domains.

Filtering is followed by feature extraction. ESMER extracts a set of features (the "feature vector") from the filtered waveforms, typically consisting of:

- standard deviation
- coefficient of kurtosis
- coefficient of skewness
- five linear prediction coefficients

The first three can be described as amplitude domain features and the last five as frequency domain features (Appendix A).

The final stage of the Extractor is "feature vector archiving". This means that the line conditions are archived together with the feature vector for a mesh of points in the liquid-gas velocity domain. Thus a data record on the archive comprises, the line identifier code, local temperature and pressure, separator temperature and pressure, separator liquid and gas flowrates and superficial liquid and gas flowrates at line conditions. ESMER uses a built in EOS package to derive the superficial liquid and gas flowrates from separator flowrates. Ideally the sensors should be placed as near to the separator as posible to minimise the effect of pressure and temperature changes.

Two methods are offered for building the feature vector archive. (This is another way of saying; there are two methods by which ESMER can be calibrated). In the active method, the operator sets the line conditions to cover a range of flow conditions. In the passive method, ESMER sits on the line, listens and learns (i.e. it builds up its archive gradually, by adding one more record, each time flow conditions change by a predefined increment under normal production conditions). In the passive methods, the key fields of the archive record (i.e. separator flowrates) and other supplementary data (i.e. separator and line pressure and temperature conditions) must also be sampled on-line through an A/D interface.

In our laboratory tests at Imperial College, feature vectors were collected on a mesh of 20*20 points across a wide range of flow regimes in 1 and 2 inch horizontal air-water flow lines. Examples of the resulting feature vector distributions are shown on the superficial gas-liquid velocity domain (the "pattern space") in Figs 2 and 3.

For an analogy with speech recognition research, each point on the mesh can be imagined to represent an individual speaker. As transitions from one regime into another is continuous the feature vector distribution ("training set") was represented in the form of contour maps.

The Categoriser

The Categoriser refers to the set of procedures by which ESMER can determine line conditions in real time (allowing a lag time for processing depending on the speed of the computers employed). This could mean identification of the flow regime, alerting to significant changes in line conditions or a direct measurement of the flowrates of individual phases. In each case output takes the form of a visual screen display.

The categoriser uses the feature vector of the measured waveform to assign it to a certain "class" in the "training set" archived by the Extractor. The key fields of the class to which the measurement is assigned, results in the required measurement. The key fields are defined and entered during the feature extraction (calibration) stage discussed above. These could be flow regime types and/or the superficial liquid and gas velocities.

Categorisers can be broadly divided into two principal areas: Conventional and Artificial Intelligence. Conventional techniques are based upon two major methodologies - statistical and structural.

So far in our study we have applied two types of classifiers which can both be classified as hybrid statistical categorisers.

One of these is named "template matching" where the measured feature vector and the template (the "feature vector of the training set") are considered to be vectors in n-dimensional space (where n is the number of features in the vector). A metric (the Euclidian norm) is used to determine the closeness of the match between the two vectors. The Euclidian distance is given by:

$$D_e^{(J)} = \sum_{i=1}^{n} \left[(M_i - P_i^{(J)}) / SD_i \right]^2 \qquad (1)$$

where $D_e^{(J)}$ is the Euclidean distance between the measured vector 'M' and the prototype pattern $P^{(J)}$. M_i and P_i are the ith feature of the measured and the prototype feature vectors and n is the number of features of the in the prototype vector set. SD_i is the standard deviation of the ith feature used to normalise the feature domains.

The other method was an intuitive graphical technique in which contour maps of the eight features were overlayed and a unique intersection "zone" was searched for the measurement (consisting a set of eight features). The bandwidth of the contours were set equal to the standard deviation of each feature (as obtained from the "training set").

ESMER has also drawn some inspiration from "artificial intelligence" techniques applied in speech identification. For example one such approach is the "context expert" system which makes a statistical prediction of the next word in a sentence based on the words preceding it. Homonyms (phrases that sound similar) are also distinguished with ease by context analysis. Consider these two sentences:

" A new display can recognise speech" and,
" A nudist play can wreck a nice beach".

Acoustic analysis might run into considerable difficulties to distinguish between these two sentences. However, contextual analysis would resolve the difficulty.

ESMER encounters similar problems in multiphase flow. Consider the following analogy:

If the categoriser has selected a certain class (e.g. "bubbly flow") for a certain waveform, then the next measurement will have high probability of being a certain other class (e.g. slug flow if the gas flow is known to be increased). ESMER consults a visual flow regime map[3] to constrain the "parameter space". For example, if an unconstrained search across all flow regimes leads to more than one equivalent (good) match, ESMER's "context expert" system can choose the correct one.

ESMER applies a standard test, known as the *F*-ratio test (Appendix B) to determine the relative strength of the features across flow regimes (Table 1). In general it was found that the standard deviation provided the strongest feature. The *F*-ratio of the features are used as weighting coefficients in the the template matching method and in deciding the order of the overlays in the contour method.

ACCURACY

The highest accuracy attainable by the ESMER in flowrate measurement will depend on the density of the calibration mesh (i.e. number of points at which the feature vector is archived). The lowest accuracy will obviously depend on the success of the match between the measured and the training - set feature vector.

An accuracy of $\pm$ 5% was achieved in extensive tests conducted with 1 and 2 inch diameter horizontal air-water rigs at Imperial College. (Figs. 4 and 5). Furthermore, it is possible to make a general appraisal of the potential capability of ESMER with reference to speech and speaker identification techniques.

If speakers utter the same words as those which make up the "training set", then current speech identification technology is capable of producing identification accuracies close to 100%. Similar accuracies are attainable in deciphering speech waveforms when the system is trained on words spoken by given speakers.

ESMER with its *in-situ* calibration bears a close resemblance to the conditions of these tests, because ESMER is founded on the premise that turbulence characteristics of multiphase flow are uniquely related to the flow rates of the individual phases in given flow lines under given conditions. In other words, given the same pipeline and fluid same flowrates should produce same turbulent characteristics at different times. If these characteristics are fully represented by the feature vector and each record on the archive ("the training set") belongs to a certain superficial liquid-gas velocity ("the key field of the record"), then the analogy is complete. Each record on the archive can be imagined to represent an individual speaker and speakers to be identified (superficial liquid-gas flowrates) are those who participated in compiling the original "training set". Provided that the "training set" is comprehensive ESMER's accuracy should be as good as those attained in speaker recognition tests.

A universal calibration (a general training set in which same words are uttered by different speakers) is not presently attainable but remains as a goal for the future.

RESPONSE TIME

The processing time of the measurements could be reduced to a matter of seconds by selection of suitable processors and improved algorithms. At present with a 386 based PC, the response time of ESMER is under 20 seconds. ESMER shows superficial liquid and gas velocities on the computer screen in real time with a simulated rotameter (Fig. 6).

APPLICATION AREAS

ESMER can find a number of applications in general fluid flow and process engineering as well as oil and gas production operations.

As an example, we can consider a principal manner of utilisation of ESMER in conjunction with a (temporary) test separator where initially, the single phase measuments provided by conventional methods are used for its calibration. The test separator can then be removed and ESMER will provide on-line measurements from that point onwards. A typical configuration is shown in Fig. 7 where it is envisaged that ESMER is calibrated to measure crude oil-gas flow from individual wells (e.g. for allocation measurement) as well as for the combined flow.

ESMER can also be used as an alarm device to indicate significant deviations away from 'normal' operating conditions in the line. For instance, ESMER will be able to detect onset of slugging in pipelines or gas kicks during well drilling.

CONCLUSIONS AND FUTURE WORK

A novel method is presented for the measurement of the flowrates of individual phases in multiphase flow. The method is based on signal analysis and pattern recognition techniques.

A turnkey system has been developed comprising a desk top computer with an A/D converter and menu driven software package for field application of the technique by the novice user. The package utilises waveforms from common differential and absolute pressure signals to build a calibration database of the hydrodynamic characteristics of the particular flow line. A passive mode of operation is available as an option whereby the calibration database can be built without any user intervention.

An accuracy of $\pm$5% was archieved in laboratory trials.

Work is now in hand in two directions. First, ESMER will be extended to measure individual flowrates of oil-gas-water in multiphase flow. Second, the accuracy of the technique will be increased by:

- Generation of new waveforms by cross correlation of signals from different sensors (such as void fraction and differential pressure sensors)

- Extraction of new features from the pressure and void fraction waveforms. At present the feature vector comprises eight features.

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APPENDIX A: STOCHASTIC FEATURES

The amplitude and frequency domain features extracted by ESMER from pressure and void fraction waveforms are presented in the following.

a. Amplitude Domain Features

The probability density function of a random signal describes the probability that the sampled data will assume a particular value within some defined range at any instant of time (Bendat and Piersol[4]). The probability density function, p (x), can be defined as follows :

$$p(x) = \lim_{\Delta x \to 0} \frac{\text{Prob}\left[x < x(t) < x + \Delta x \right]}{\Delta x}$$

$$= \lim_{\Delta x \to 0} \frac{1}{\Delta x} \left[\lim_{T \to \infty} \frac{T_x}{T} \right] \qquad (1)$$

where p (x) is the probability density function of a sample time history record x (t), T_x is the time at which the time history record x(t) takes a value between x and x+Δx and T is the observation time. The moments associated with the probability density function can be used as descreptive measures of the distribution. These moments are the mean (first moment about the origin), the standard deviation (second moment about the mean), the coefficient of skewness (third moment about the mean) and the coefficient of kurtosis (fourth moment about the mean). The mean, $\overline{x}$, is the average value of the data points and can be defined as follows :

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{(n-1)} \qquad (2)$$

where n is the total number of points in the sampled record. The standard deviation is the root mean square of the deviations from the arithmetic mean and is a measure of the dispersion of the data. The standard deviation, SD, is defined as :

$$SD = \left[\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{(n-1)} \right]^{0.5} \qquad (3)$$

When a distribution is not symmetrical about its mean value, it is said to be skew. If the tail of the distribution is longer on the right of the mode (the highest point on the distribution), the distribution is said to be skewed to the right or to have positive skewness. Similarly, if the tail is longer on the left, the distribution is skewed to the left or has negative skewness. The coefficient of skewness, CS, is defined as :

$$CS = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^3}{(n-1)\ (SD)^3} \qquad (4)$$

Kurosis is the peakedness of a distribution. The normal curve is taken as the standard of peakedness. A curve less peaked than the normal is said to be platykurtic and a more peaked curve is said to be leptokurtic. The coefficient of kurtosis, CK, is defined as :

$$CK = \left[\frac{\sum_{i=1}^{n} (x_i - \bar{x})^4}{(n-1)\ (SD)^4} \right] - 3 \qquad (5)$$

b. Frequency Domain Features

A new frequency domain analysis technique for two-phase gas-liquid flow waveforms has been utilised in this system. Atal and Hanauer[5] introduced the linear prediction method in speech processing which became increasingly dominant in speech analysis. Makhoul[6] presented a very informative review of the technique which will be briefly described in the following.

Linear prediction provides a simple and effective method to obtain the main characteristics of the spectral density function of the signal. In this technique, the signal is modeled as a linear combination of its past values and past and present values of a hypothetical input to a system whose output is the given signal. According to this model, the signal, x_t, can be represented in the following form :

$$x_t = -\sum_{k=1}^{p} a_k x_{t-k} + G \sum_{l=0}^{q} b_l u_{t-l}, \quad b_0 = 1 \qquad (6)$$

where a_k, $1 \le k \le p$, b_l, $1 \le l \le q$, and the gain G are the parameters of the hypothesized system with some unknown input u_t. Equation (6) can be rewritten in the frequency domain by taking the Z-transform of both sides that yields :

$$H(z) = \frac{X(z)}{U(z)} = G \frac{1 + \sum_{l=1}^{q} b_l z^{-l}}{1 + \sum_{k=1}^{p} a_k z^{-k}} \qquad (7)$$

where

$$X(z) = \sum_{t=-\infty}^{\infty} x_t z^{-t} \qquad (8)$$

is the Z-transform of x_t, U (z) is the Z-transform of u_t and H (z) is the transfer function of the system, which is the general pole-zero model. The roots of the numerator and denominator polynomials are the zeros and poles of the model respectively. There are two special cases of the model which are : 1) all-zero model where $a_k = 0$, $1 \le k \le p$; 2) all-pole model where $b_l = 0$, $1 \le l \le q$. The following section will be confined to the all-pole model which is going to be implemented in the current study.

In the all-pole model, equations (6) and (7) are reduced to:

$$x_t = -\sum_{k=1}^{p} a_k x_{t-k} + G u_t \qquad (9)$$

$$H(z) = \frac{G}{1 + \sum_{k=1}^{p} a_k z^{-k}} \qquad (10)$$

Since the output, u_t, is totally unknown, the output signal, x_t, can only be approximately predicted from previous samples, i.e.

$$\tilde{x}_t = -\sum_{k=1}^{p} a_k x_{t-k} \qquad (11)$$

Where $\tilde{x}_t$ is the approximation of x_t. The difference between the actual value x_t and the predicted value $\tilde{x}_t$ is called the residual error, e_t, which is given by :

$$e_t = x_t - \tilde{x}_t = x_t + \sum_{k=1}^{p} a_k x_{t-k} \qquad (12)$$

The predictor coefficients, a_k, should be adapted to minimise the error signal, e_t, which is achieved by the minimisation of the total squared prediction error with respect to the coefficients. The total squared error, E, is defined as :

$$E = \sum_t e_t^2 = \sum_t \left(x_t + \sum_{k=1}^{p} a_k x_{t-k}\right)^2 \qquad (13)$$

To minimize E with respect to each of the coefficients, equation (13) is differentiated with respect to a_i and set the resulting derivatives to zero. The minimum total squared error, E_p, can finally be given as :

$$E_p = \sum_t x_t^2 + \sum_{k=1}^{p} a_k \sum_t x_t x_{t-k} \qquad (14)$$

By solving the set of p equations, given in equation (14) in p unknowns, the linear prediction coefficients a_k which minimise the total squared error can be obtained. Makhoul[6] and Witten[7] give a thorough review of the methods used for the estimation of the linear prediction parameters. The linear prediction technique is to be implemented in the field of two-phase flow in a similar way to that applied in speech analysis. Since it provides a simple and effective method of representing different signals in terms of a small number of parameters, the linear prediction method can be used not only as a way of data compression but also as a supply for different statistical features of the different two-phase flow conditions.

APPENDIX B: The *F*-ratio

In order to evaluate the selected statistical features in terms of their ability to discriminate the different flow conditions over the ranges of superficial gas and liquid velocities investigated in this study, the *F*-ratio used by Atal[8], in automatic speaker recognition was implemented. For a single statistical feature, the *F* ratio has been defined as :

$$F = \frac{\text{variance of speaker means}}{\text{average within speaker variance}}$$

$$= \langle[\overline{x}_i - \overline{\mu}]^2\rangle_i / \langle[x_\alpha^{(i)} - \overline{x}_i]^2\rangle_{\alpha,i} \qquad (15)$$

In our case of two-phase gas-liquid flow in pipelines, the "speaker" in the *F* ratio equation will be substituted by "flow condition". In equation 15, $x_\alpha^{(i)}$ is the feature value from the αth block of the signal representing the ith flow condition, which may be regarded as samples from a probability distribution associated with that specific flow condition. The symbol $\langle\ \rangle_i$ indicates averaging over various flow conditions, $\langle\ \rangle_\alpha$ indicates averaging over the different blocks of a single flow condition and $\overline{x}_i$ is the estimated mean value of the feature for the ith flow condition, i.e.

$$\overline{x}_i = \langle x_\alpha^{(i)} \rangle_\alpha \qquad (16)$$

Finally, $\overline{\mu}$ is the overall mean value of the feature averaged over all flow conditions, i.e.

$$\overline{\mu} = \langle \overline{x}_i \rangle_i \qquad (17)$$

It is obvious that for accurate recognition, a good feature is one for which the distributions of the different flow conditions are concentrated at widely different locations in the feature space. Consequently, the more suitable the feature, the higher the value of *F*.

Table 1 *F*-ratio of absolute and differential pressure signal features

Feature	*F*-ratio			
	Absolute pressure	Radial differential	Axial - differential 1 D	Axial - differential 8.4 D
SD	29.0	53.2	39.6	60.5
CS	2.00	0.28	0.12	1.66
CK	0.63	0.76	0.53	1.18
V_p	2.90	5.09	3.42	2.79
a_1	5.30	5.48	6.29	2.01
a_2	4.00	2.23	6.61	1.15
a_3	2.00	0.95	2.21	0.57
a_4	1.90	2.10	4.07	0.94

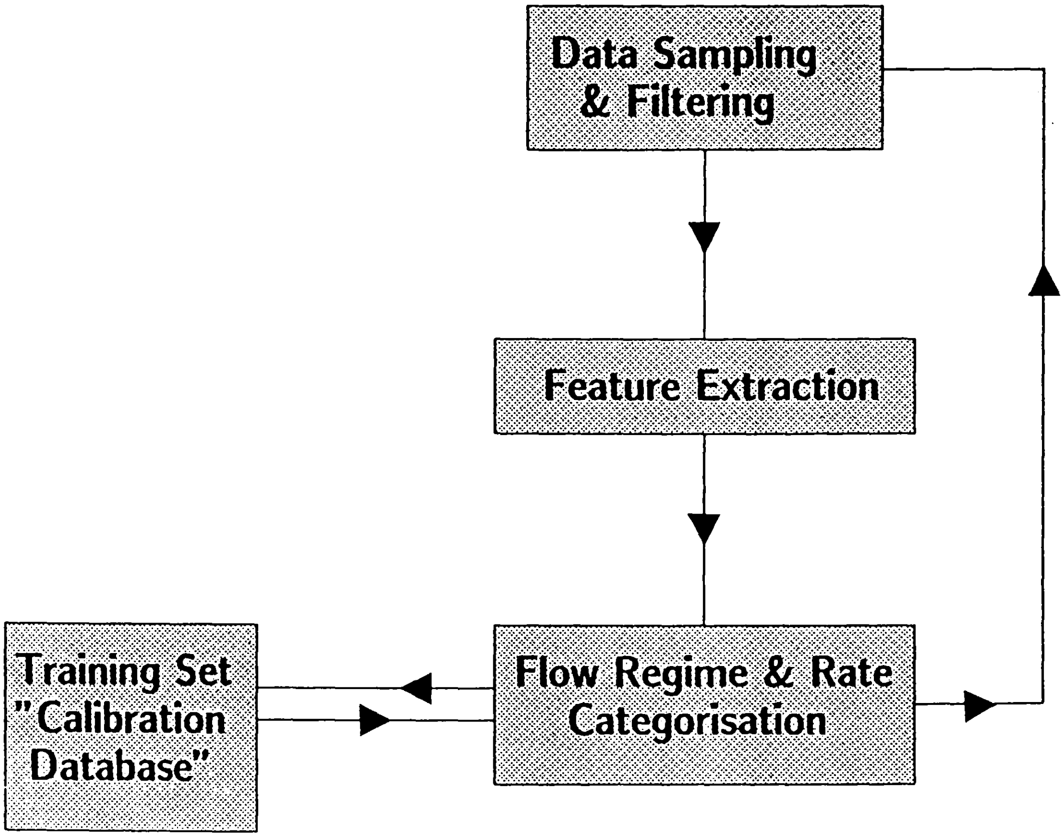

Fig. 1 ESMER's Block Diagram

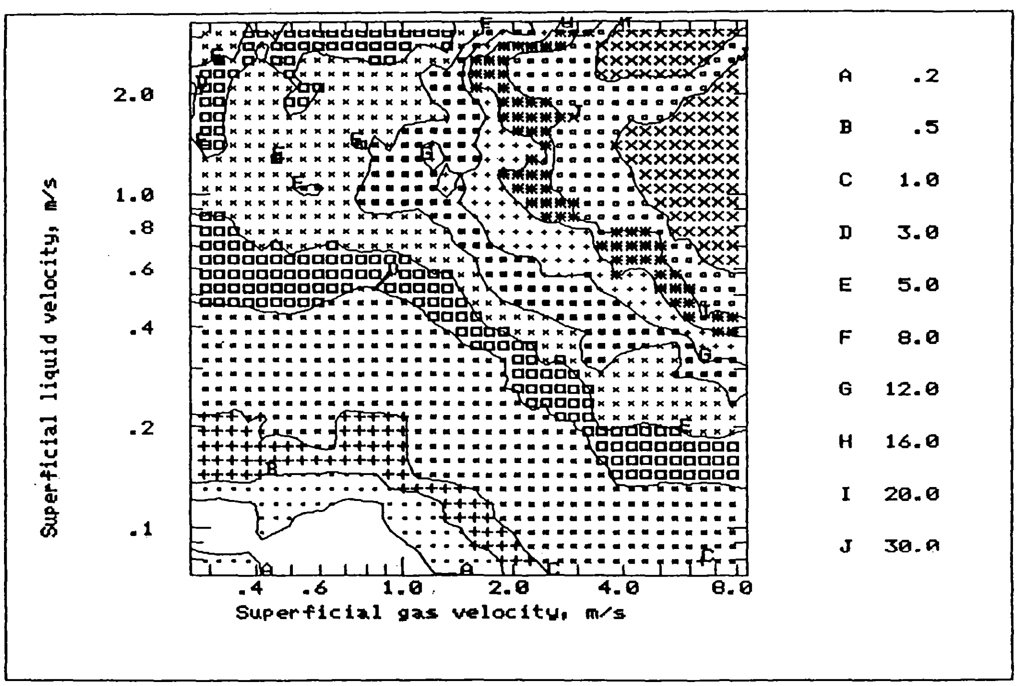

Fig. 2 The standard deviation distribution of the radial differential pressure signal.

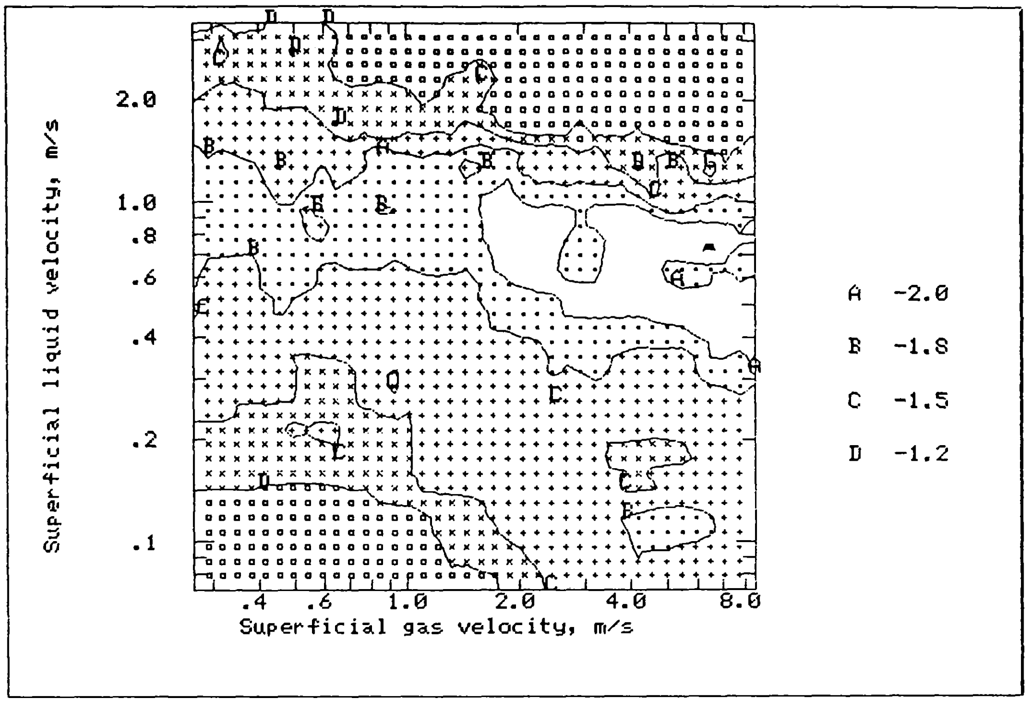

Fig. 3 The linear prediction coefficient a_1 distribution of the radial differential pressure signal.

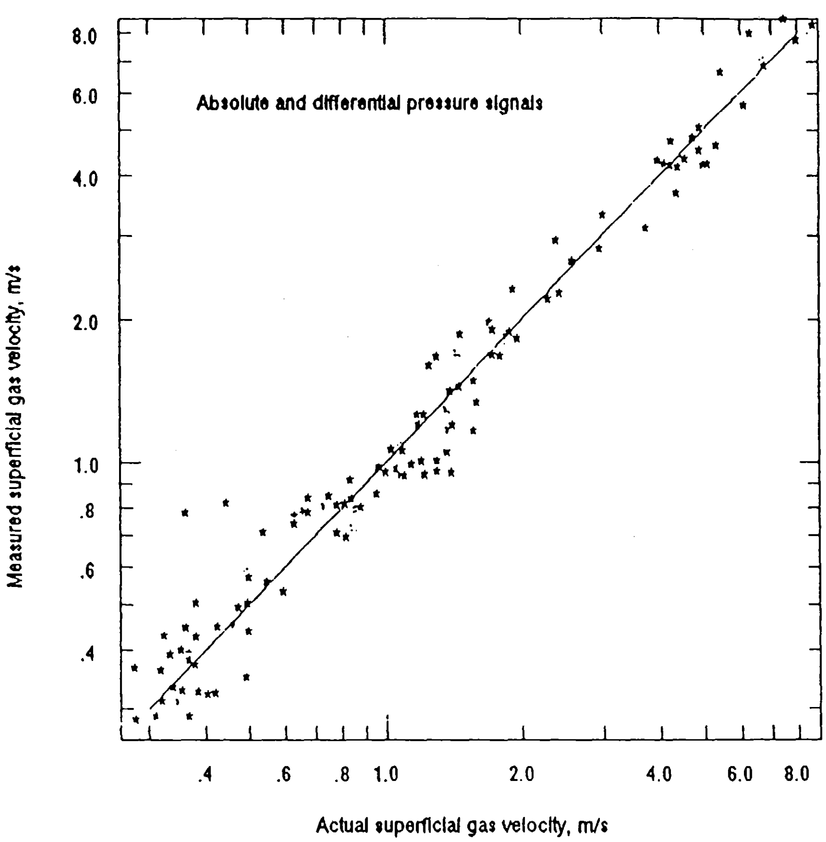

Fig. 4 Error in superficial gas velocity measurement

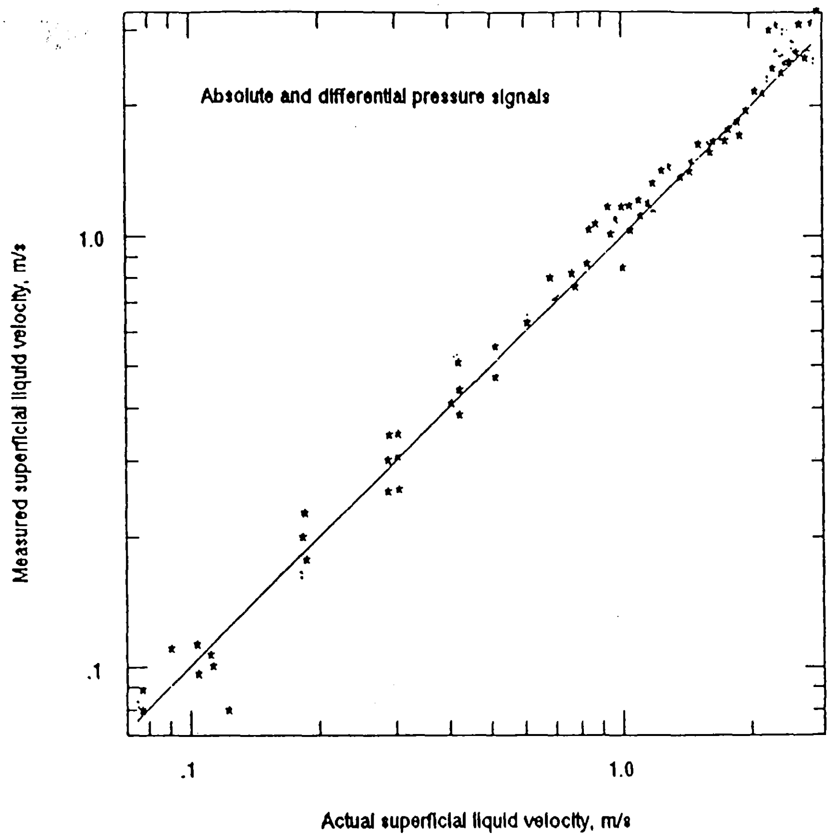

Fig. 5 Error in superficial liquid velocity measurement

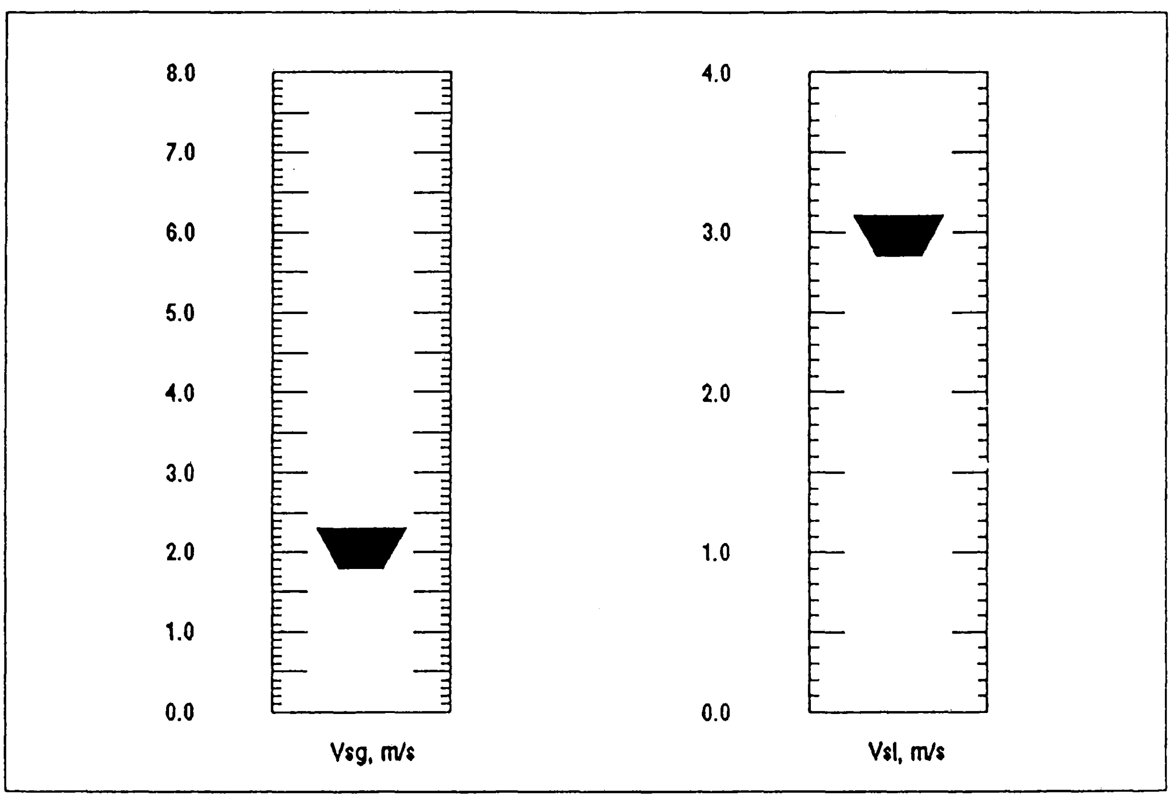

Fig. 6 ESMER's computer screen output.

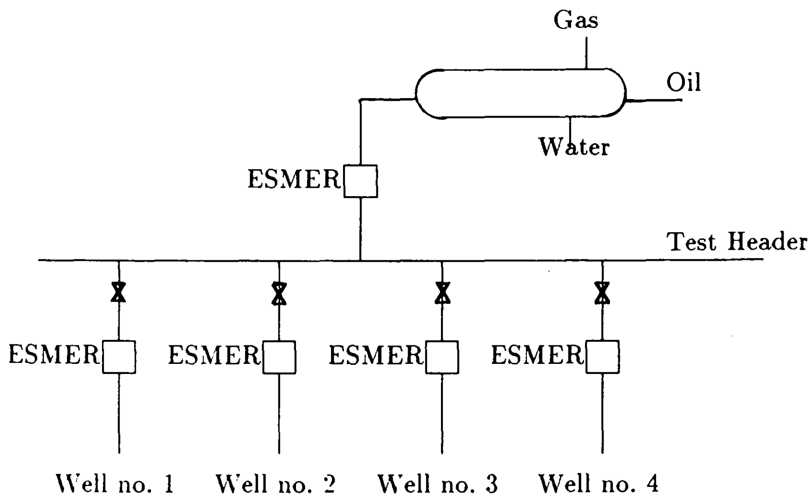

Fig. 7 An example of ESMER's application in multiphase flowrate measurement