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Characterization of the turbulence properties of wet gas flow in a V-Cone meter with neural nets

Haluk Toral, Shiqian Cai, Petroleum Software Ltd
Richard Steven, Robert Peters, McCrometer

1. INTRODUCTION

This paper presents the latest results from the ongoing development of the neural nets with the V-Cone meter, in wet gas, by Petroleum Software Ltd (PSL). In the paper the results from wet gas tests in the NEL facility will be presented and also from tests in K-Lab which Shell were good enough to allow us to include. These set of tests expand the data base for this development.

2. METHODOLOGY

In simple mathematical notation the present methodology can be described as follows:

Flow rates of individual phases
= function of (momentum transfer characteristics, flow meter characteristics, fluid properties, pipeline properties)
(1)
where,
momentum transfer characteristics
= function of (stochastic features derived from high frequency wave forms) (2)

Back propagating supervised neural networks were used to establish the two non-linear relationships to relate the flow rates of individual phases directly to the stochastic features of the flowing fluids. In neural net 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 of relationship 2 represent the training inputs. The wave forms in relation 2 can emanate from any sensor which responds to fluid turbulence. In this investigation, the stochastic features of the flow were derived from differential pressure and absolute pressure sensor signals around the V-cone.

The features input into the neural nets can take multiple forms, including 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).

Not all stochastic features carry the same influence in characterisation of the flow conditions. The optimum combination of features can be determined empirically by means of the F- ratio and saliency tests [2]. The saliency test is carried out most conveniently by means of the neural net itself by observing the sensitivity of the targets to variations in input features. Visual inspection of the signals and the distribution of the features across the liquid – gas surface are also recommended for a qualitative assessment of the discriminating capability of the signals. The time series of the signal must show a modulation which reveals the influence of liquid loading in the wet gas stream (Figure 1). Ideally on the liquid –gas contour maps, effective features will show steep gradients in either liquid or gas directions (Figure 2).

The neural net 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 the Factory Calibration a plurality of stochastic features derived from the sensor signals are trained with a supervised neural net against a plurality of reference measurements of individual phase flow rates. The weights of the neural nets, called the Factory Calibration, are preloaded on the flow computer in an industrial application.

For ease of reference in some parts of this paper the acronym ESMER (Expert System for Multiphase Metering) will be used to refer to the methodology described above.

3. TEST CONDITIONS AT NEL AND K-LABS

The methodology described above was evaluated for its suitability for wet gas measurement with V-cone meters in laboratory tests conducted at NEL and Statoil K-lab wet gas loops. The test conditions are summarized in Table 1

	Pressure Bar (number points)	Condensate/Oil Kg/m3	Water Kg/m3	Gas/Nitrogen Kg/m3
K-Lab	25 (48)	698.2749	992.5497	20.6162
	55 (81)	676.1818	992.2661	44.7896
	90 (82)	649.3265	993.2953	76.6442
NEL	15 (30)	806.979		18.15
	60 (30)	807.060		72.13

NEL tests were conducted in May 2003. 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 (Druck) and a portable PC as the data acquisition system (PC). The test fluids were domestic fuel 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. Figure 3 shows the distribution of liquid and actual gas flow rates for the NEL tests on the Mandhane flow regime map.

K-labs tests were conducted in February 2004. A 6" V-cone meter with a beta ratio of 0.7414 was installed in a horizontal test section and connected to high frequency absolute and differential pressure gauges (Druck). Test fluids were field gas, condensate and water from Statoil gas terminal at Norway. The test matrix comprised gas flow rates at 200, 400, 600 up to1000 m^3/hr at 25 , 55 and 90 bar. For each gas and pressure combination, a set of liquid flow rates were passed corresponding to Lockhart-Martinelli parameter from 0, to 0.32 (GVF from 100% to 90.7%). Water contents in the liquid were also varied from 10, 20,30, 60 up to 90%. Figure 4 shows the distribution of liquid and actual gas flow rates for the K-Lab tests on the Mandhane flow regime map.

4. ANALYSIS

V-cone differential pressure signals were sampled and analysed by the methodology described above. The essence of the methodology is to extract characteristic features from fluctuating differential and absolute pressure signals sampled at high frequencies. The features are then related to the flow rates of individual phases by neural nets. The tests aimed to establish whether such features could be related to liquid loading in wet gas flow and whether the neural net models can be generalised between different test loops. In the past, the same methodology has been applied in multiphase flow rate measurement up to 97% GVF [2-4] Thus the principal objective of the present series of wet gas tests is to find out the limits of detection and characterisation of such fluctuations with diminishing liquid loading.

The analysis started with a conventional correlation of the data as DP Over-reading vs Lockhart-Martinelli Parameter (X), as shown in Figure 5 for an appraisal of the consistency of the data.

Next, we investigated the most effective features and targets for training the neural net by means of the saliency test [3]. Features under investigation were derived from the amplitude and frequency domains. We have noted that some of the frequency domain features exhibited inverse trends with increasing X between NEL and K-Labs and these were ruled out from further consideration.

As targets (neural net outputs) we have tried three pairs:

1. Volumetric flow rate of gas/liquid
2. Mass flow rate of gas/liquid
3. Overreading/Lockhart Martinelli Parameter

It should be noted that targets are recommended to be chosen in pairs as experience has shown this to be more effective for the convergence of the neural nets [3].

We have noted that the best results were obtained with volumetric flow rates of gas/liquid although the differences were within the range of statistical scatter. In this report the results of the tests are presented for volumetric flow rates only.

In each instance (ie for the above pairs of targets), the effectiveness of the neural net models were judged by a number of tests with increasingly demanding objectives. These tests can be summarized as follows:

1. Self Test: Train and test a neural net with a set of points obtained on the same test loop at a single pressure level.

2. Repeatability Test: Train a neural net with a set of points obtained on the same test loop at a single pressure level and test with repeat measurements (obtained at the same operating conditions as the training set) not included in the training.

3. Independent Test Under One Set of Conditions at One Location: Train a neural net with a set of points obtained on the same test loop at a single pressure level and test against a set of measurements (different matrix points) not included in the training.

4. Independent Test Under Multiple Conditions at One Location: Train a neural net with a set of points obtained on the same test loop at multiple pressure levels and test against a set of measurements (different matrix points) not included in the training.

5. Generalised Model (Multiple Conditions and Multiple Locations) : Train a neural net with a set of points obtained from two different loops at different pressures and test against a set of measurements (different matrix points) not included in the training.

As mentioned above the tests were repeated for a number of different features (inputs) and targets (outputs) to determine the optimum selection of features and targets

The results can be summarised in the following tables and corresponding figures.

The tables show the standard deviation of a set of sample points. We would like to note that while we quote standard deviation to two decimal places, the sample sets are small and one rogue point can exert a large influence.

Self test results shown in Table 1 and Figures 6 – 9 were carried out with one set of data (K-Labs at 25 bar) but the results are representative of our findings for other data sets which are not shown here for the sake of conciseness. Self tests results show that the neural nets converge quite well across all flow conditions.

Table 1 - Self Test (Figures 6 -9)

	RMS (%)			
K-Labs 25 bar	**Full range**	**Low Liquid X<0.1**	**Medium Liquid 0.1<X<0.2**	**High Liquid X>0.2**
Liquid	7.89	10.08	2.33	1.11
Gas	0.62	0.58	0.52	0.78
Number of Points	25	15	5	5

Repeatability tests shown in Table 2 and Figures 10 – 13 were also carried out with one set of data (K-Labs at 25 bar) but the results are also representative of our findings for other data sets. The repeatability of the gas flow rate prediction is not too different from self tests. However, the deterioration of the liquid rate prediction is noticeable.

Table 2- Repeatability Test (Figures 10 – 13)

	RMS (%)			
K-Labs 25 bar	**Full range**	**Low Liquid X<0.1**	**Medium Liquid 0.1<X<0.2**	**High Liquid X>0.2**
Liquid	13.96	15.72	14.35	5.23
Gas	0.64	0.65	0.58	0.69
Number of Points	25	15	5	5

Independent tests shown in Table 3 were also carried out with one set of data (K-Labs at 90 bar) but the results are also representative of our findings for other data sets. There were a total of 90 points at 90 bar. A set of 72 points were chosen for training the net work and 18 points were used for testing. The training and testing points were chosen at random and the exercise was repeated for a different set of points. The results shown in Table 3 are representative of our findings with different data sets. No graphics are shown for visual representation of this table in this report for lack of space. As expected, some deterioration has resulted in the prediction of both the liquid and gas rates. However, it should be noted that under the conditions of this particular study, the measurement difficulty experienced is close to the challenge of a field measurement as the training and testing sets are completely separated.

Table 3 - Independent Test for K-Labs 90 Bar

	RMS (%)			
K-Labs 90 bar	**Full range**	**Low Liquid X<0.1**	**Medium Liquid 0.1<X<0.2**	**High Liquid X>0.2**
Liquid	25.94	34.09	17.17	22.89
Gas	3.17	1.63	1.59	4.66
Number of Points	18	6	5	7

A study was also made for an Independent Test Under Multiple Conditions at One Location. The results of this study is not included here because these were between those shown in the next study and those shown in Table 3.

Next we have trained the neural net with a random set of 90 points at 55 and 90 bar from K-labs and 12 points at 60 bar from NEL The neural net was tested against a random set of 34 K-lab and 11 NEL points not included in the training set. The results displayed in Table 4a show that the gas rate prediction can be considered to be good across all liquid loadings but the prediction of the liquid rate varies from an RMS of 68.68% at low liquid loading (X<0.1) to RMS of 18.84 at high liquid loading (X>0.2). The test shows that data from different flow laboratories and flow conditions can be accommodated by the neural net model. It should be remembered that the present test conditions exhibit wide ranging conditions as the sample sets contain data points from different laboratories utilizing different fluids. The properties of the fluids were embedded in the input features of the neural nets to adapt the neural nets to different conditions.

Table 4 a- Generalised Model (Figures 14-17)

	RMS (%)			
NEL and K-Labs 55-90 bar	**Full range**	**Low Liquid X<0.1**	**Medium Liquid 0.1<X<0.2**	**High Liquid X>0.2**
Liquid	46.06	68.68	21.28	18.84
Gas	2.75	3.35	1.57	2.65
Number of Points	45	18	10	17

Table 4 b Distribution of Training and Testing Points

Training Data Set		**Testing Data Set**	
K-Labs 55-90 bar	**NEL 60 bar**	**K-Labs 55-90 bar**	**NEL 60 bar**
90	12	34	11
102		45	

Further observation of the results have shown that gas and liquid error is inversely correlated for each pair of observations (ie for a pair of liquid and gas prediction at a given operating point; if gas is over predicted then liquid is under predicted and vice versa). This meant that the prediction of the total flow rate by the neural net could be better than the error exhibited by the liquid phase alone. Thus, for the 45 observations in hand, the RMS deviation between the prediction and total reference mass rate was found to be 6.34% (Figure 18 and 19).

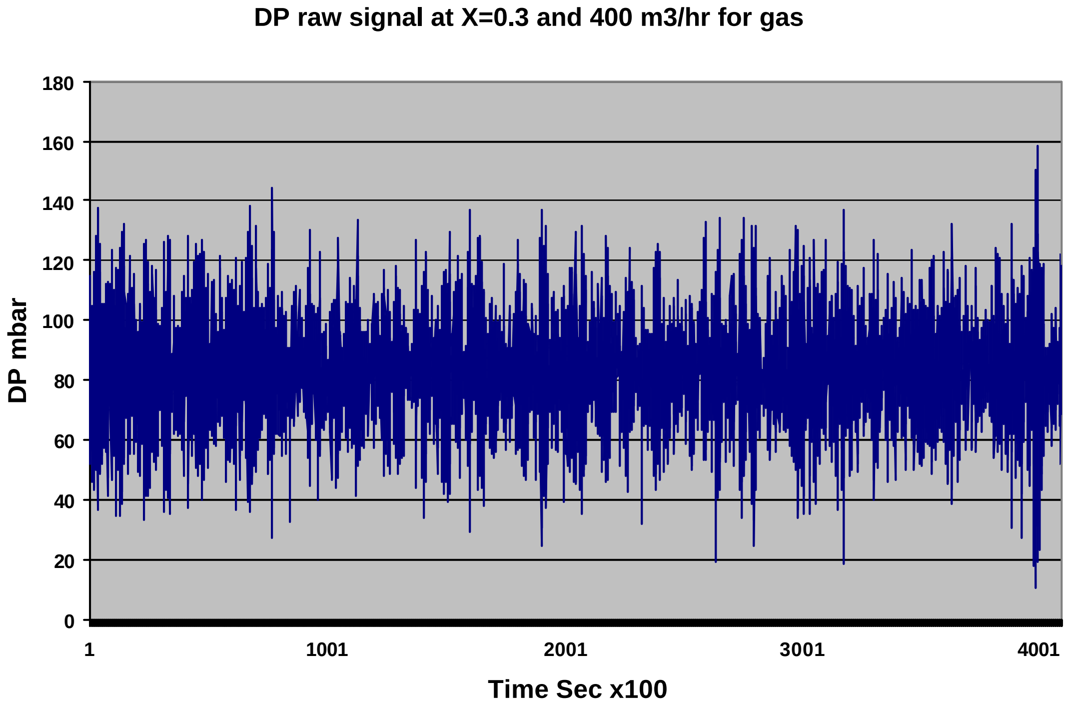
We have also observed that under and over predictions are evenly balanced across different observations (as the neural nets showed an evenly distributed and unbiased error in under and over predictions). Thus, the relative error in accumulated flow rate prediction (sum of 45 observations) was reduced considerably as follows:

- Gas volumetric flow rate relative error=1.35%
- Liquid volumetric flow rate relative error=-2.09%
- Total Mass Relative Error=-0.53%

5. CONCLUSIONS

The following conclusions have been reached from the analysis of data gathered at NEL and K-lab wet gas loops with V-cone meters:

1. A neural net can be used for flow modeling, connecting as inputs the stochastic features derived from the V-cone differential and absolute pressure signals, and as outputs the volumetric flow rates of liquid and gas phases.
2. In self tests applied with closed data sets at a given pressure level and flow loop, the model converged with an RMS error of under 1% for the gas phase and 15% for the liquid phase.
3. The model could be generalized whereby data from different flow loops at different pressures could be used for training. Tests with a set of 45 points not used in the training (and covering the full range of flow rates) resulted in an RMS error of under 3% for the prediction of the gas flow rate and under 50% for the prediction of the liquid rate. The liquid prediction accuracy improved to under 20% RMS at higher liquid loading above X>0.2 but the gas flow rate prediction accuracy was not found to be particularly sensitive to liquid loading.
4. For the same tests as those described under (3), the cumulative relative error was only +1.35% for the gas phase and -2.09% for the liquid phase. The cumulative relative error for total mass prediction was out by only -0.53%. The discrepancy between the RMS and cumulative relative error can be attributed to the fact that over and under predictions made by the neural net were spread evenly on two sides of the reference measurement.



6.

Figure 1a. Time Series of the DP Signal sampled at 800Hz (High Liquid/Low Gas)

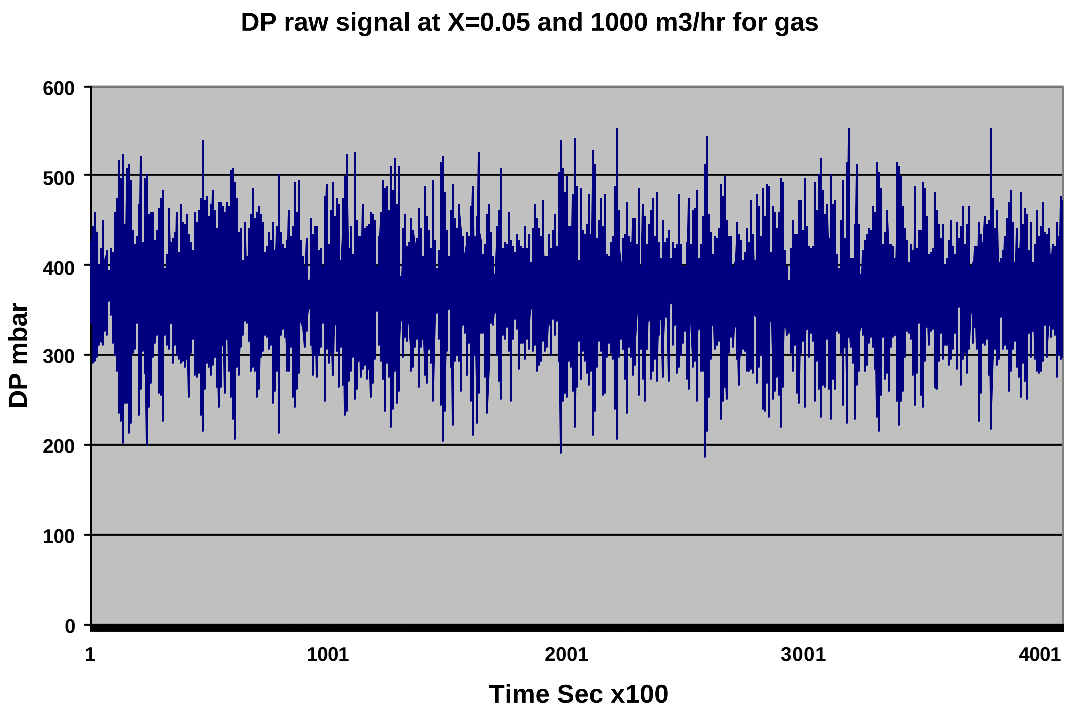


Figure 1b. Time Series of the DP Signal sampled at 800Hz (Low Liquid/High Gas)

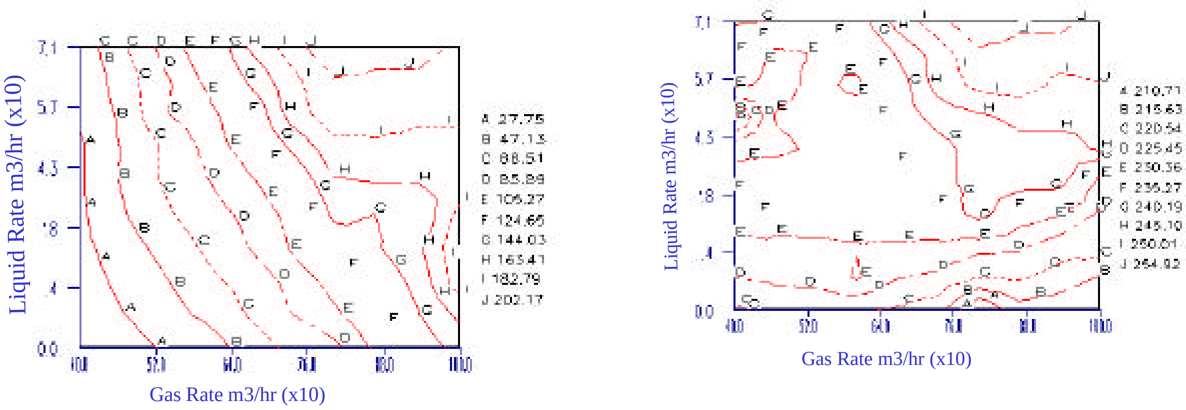


Figure 2 Contour maps of two features of the differential pressure signal

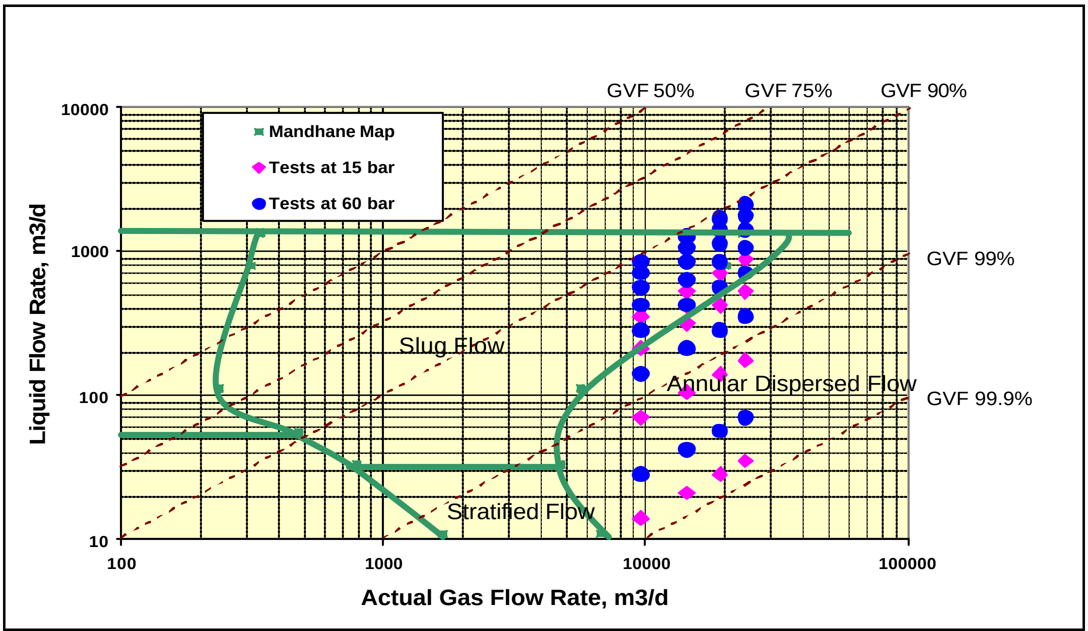


Figure 3. Operating Envelope NEL - Test Points on Mandhane Map

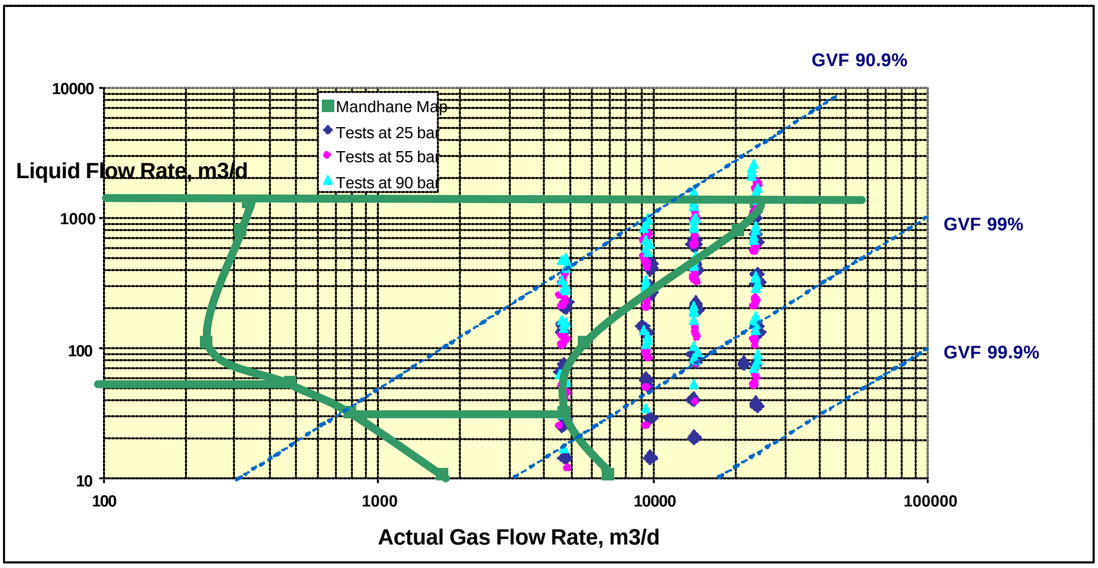


Figure 4. Operating Envelope K-Labs - Test Points on Mandhane Map

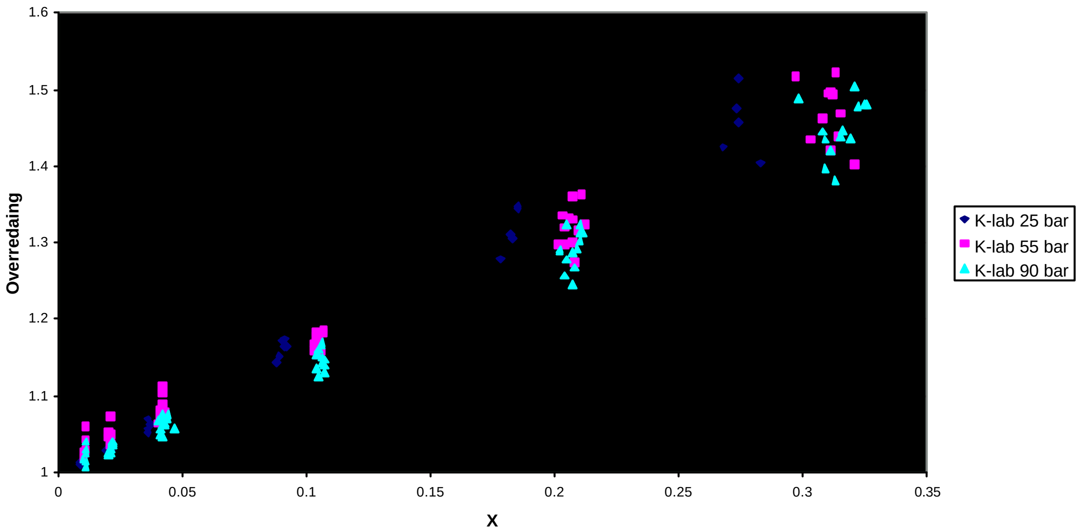


Figure 5. Over-reading of wet gas test data

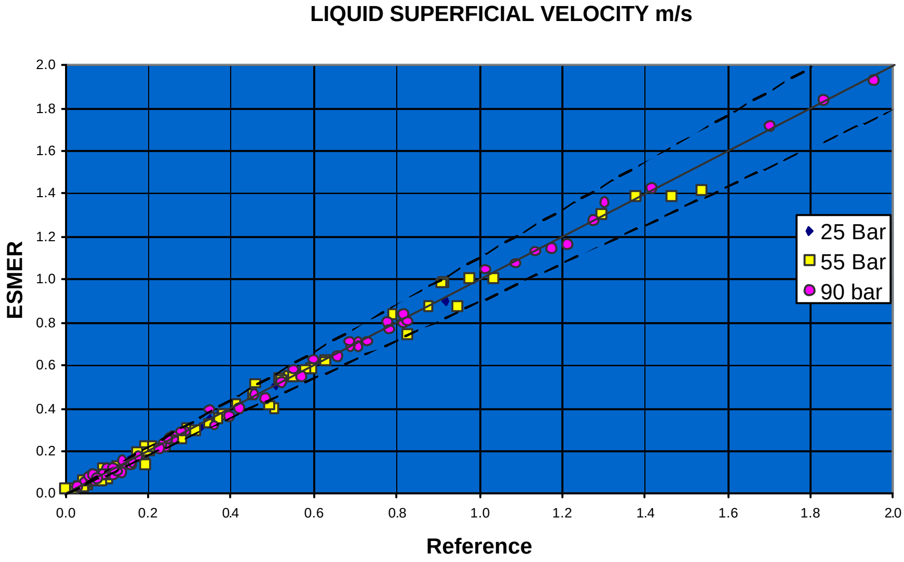


Figure 6. Liquid Flow Rate - ESMER vs Reference (Self Test)

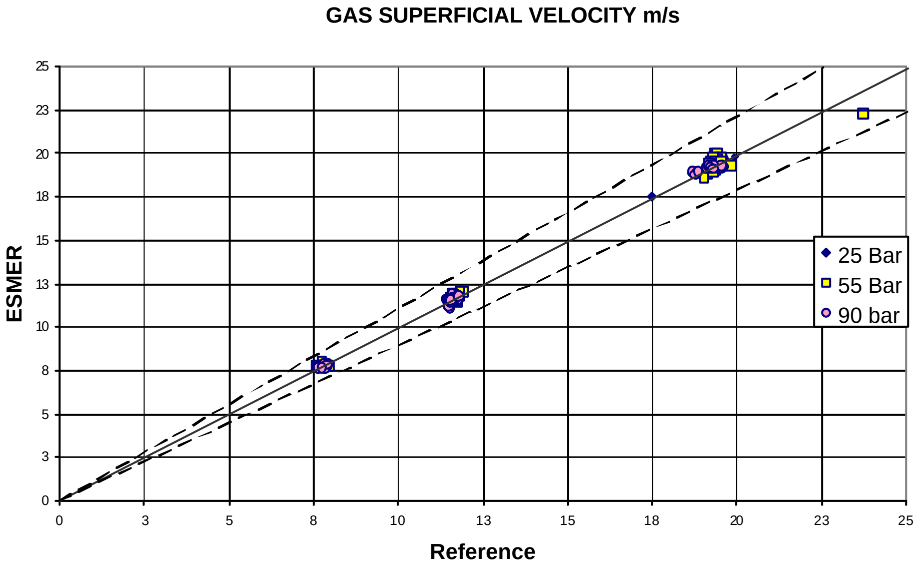


Figure 7. Gas Flow Rate - ESMER vs Reference (Self Test)

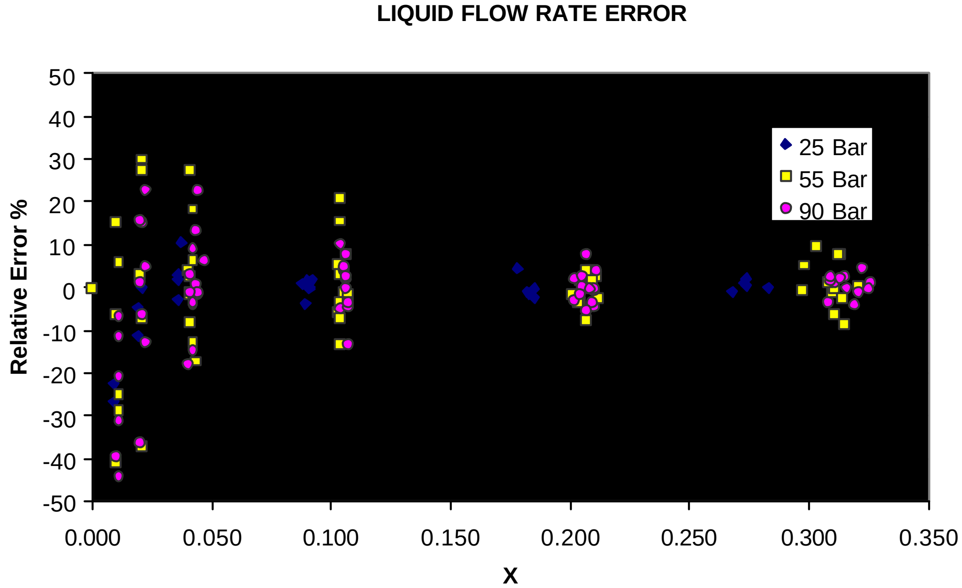


Figure 8. Liquid Flow Rate Relative Error vs. Lockhart-Martinelli (Self Test)

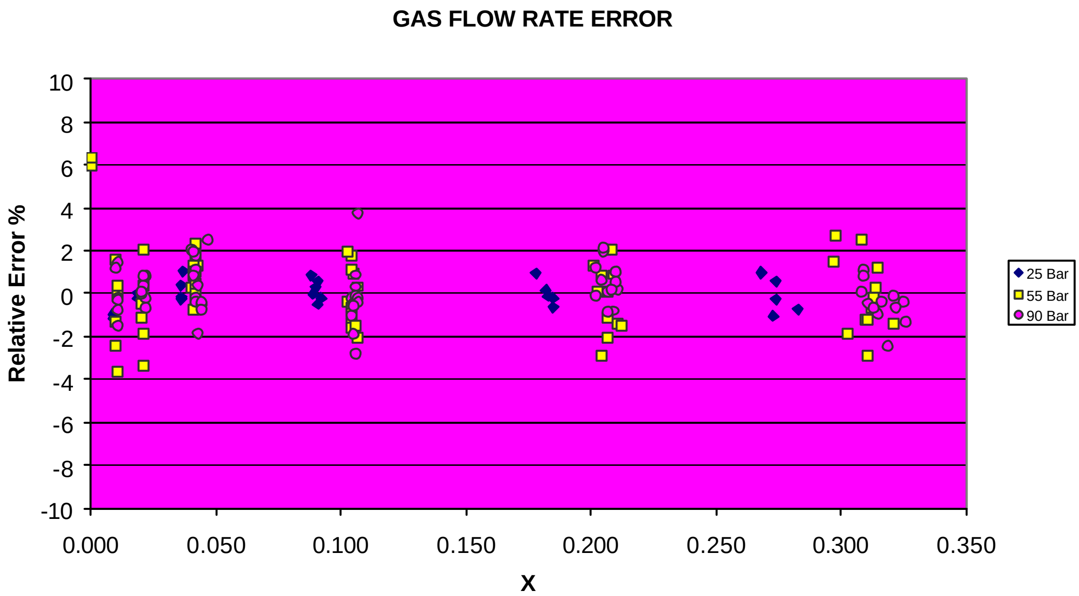


Figure 9. Gas Flow Rate Relative Error vs. Lockhart-Martinelli (Self Test)

LIQUID SUPERFICIAL VELOCITY m/s

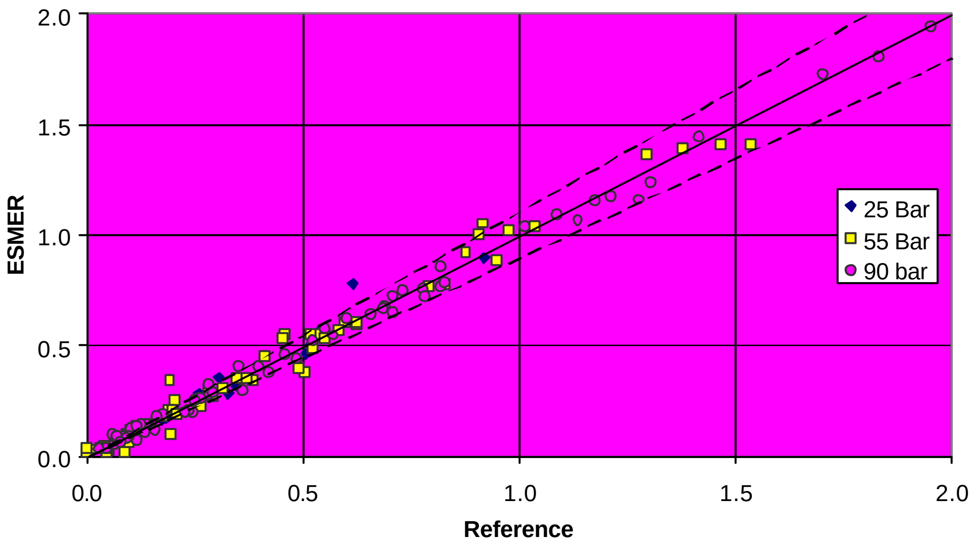


Figure 10. Liquid Flow Rate - ESMER vs Reference (Repeatability)

GAS SUPERFICIAL VELOCITY m/s

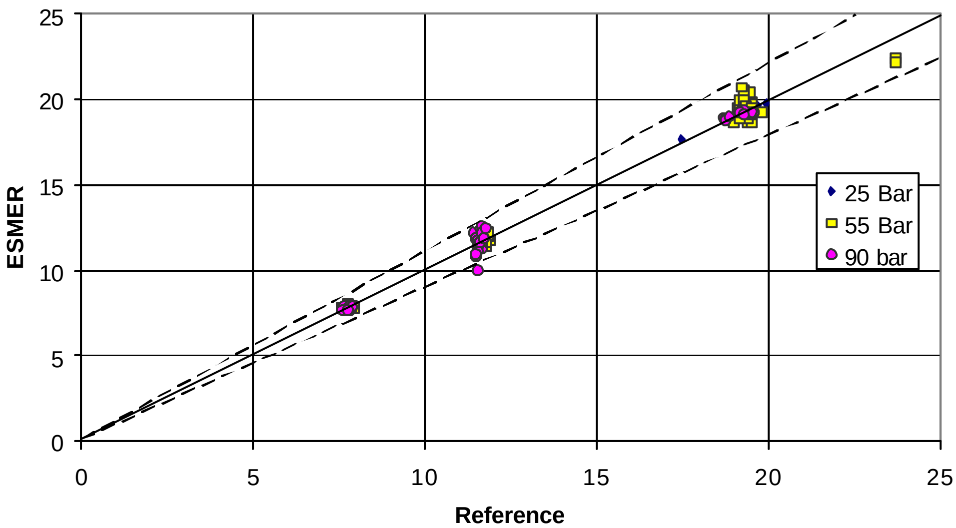


Figure 11. Gas Flow Rate - ESMER vs Reference (Repeatability)

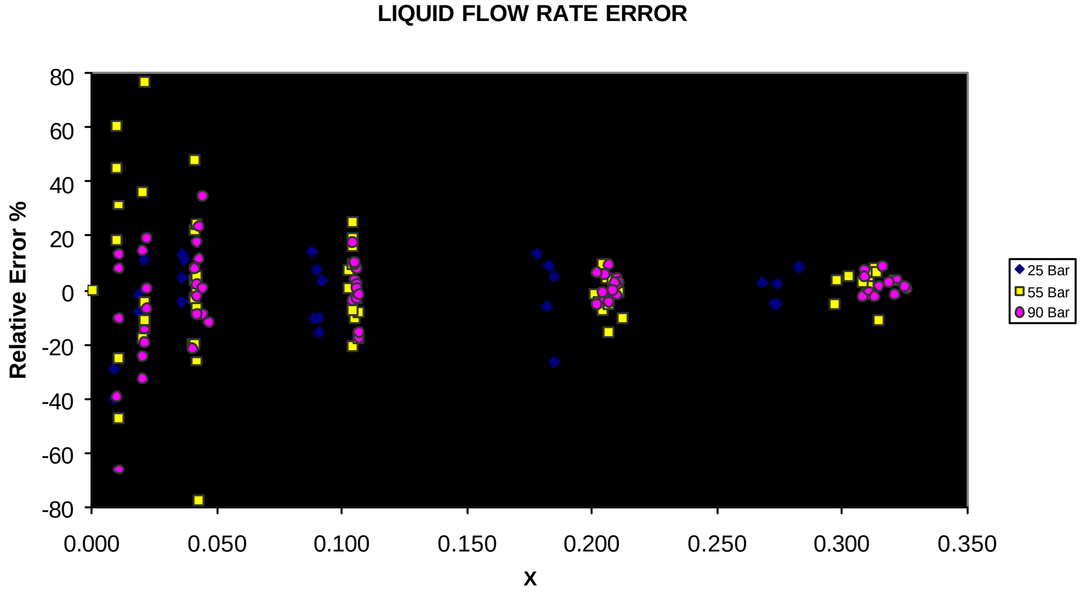


Figure 12. Liquid Flow Rate Relative Error vs. Lockhart-Martinelli (Repeatability)

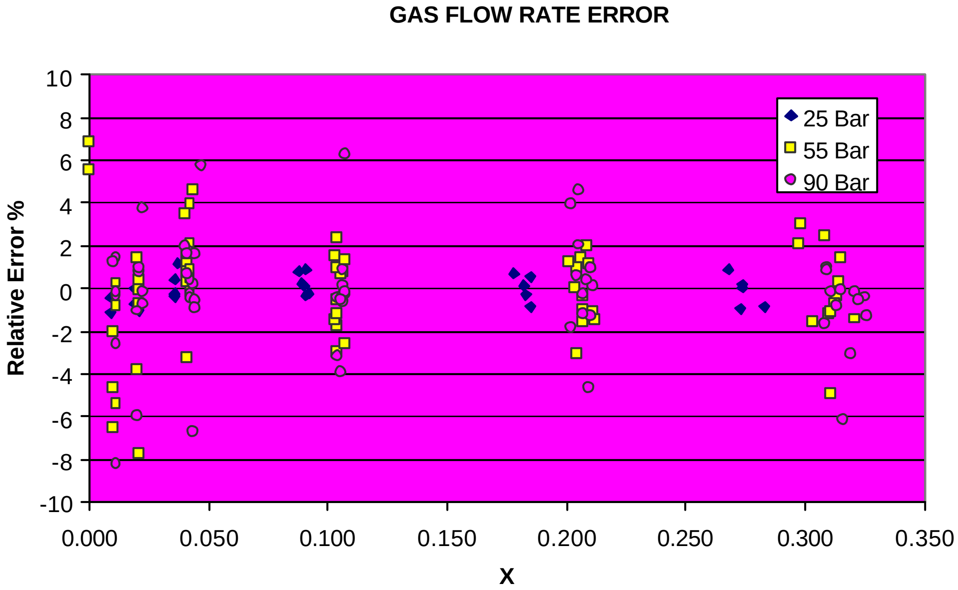


Figure 13. Gas Flow Rate Relative Error vs. Lockhart-Martinelli (Repeatability)

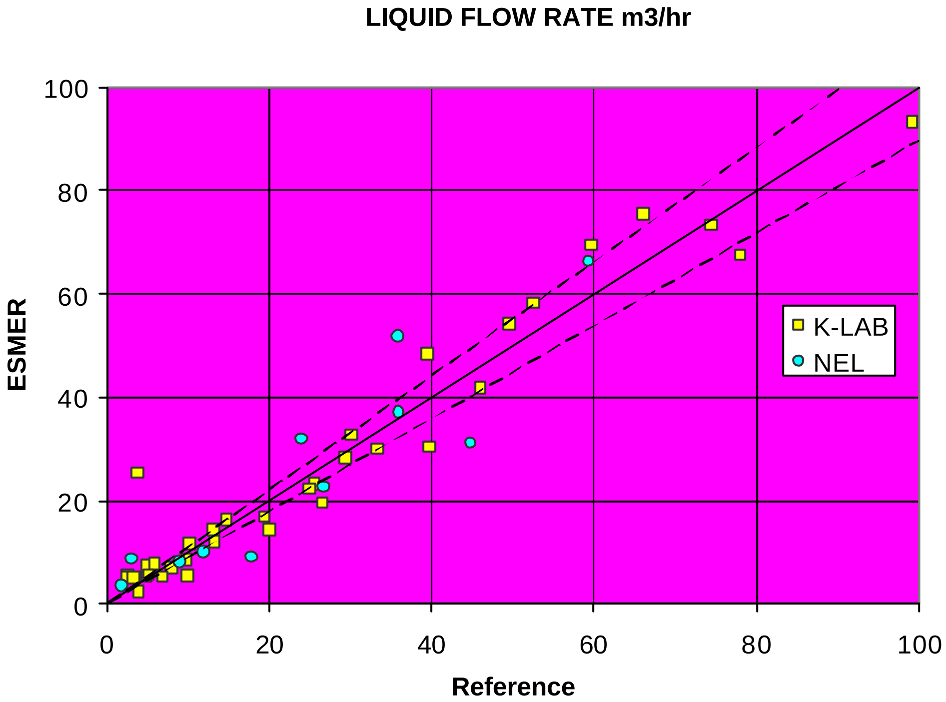


Figure 14. Liquid Flow Rate - ESMER vs Reference (K-Labs+NEL General Model)

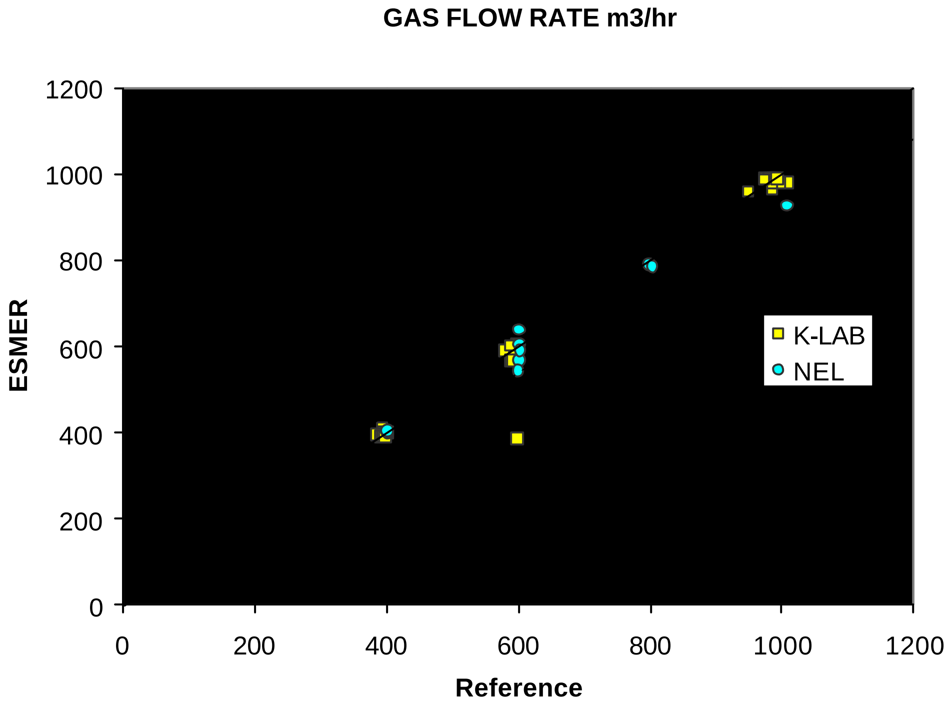


Figure 15. Gas Flow Rate - ESMER vs Reference (K-Labs+NEL General Model)

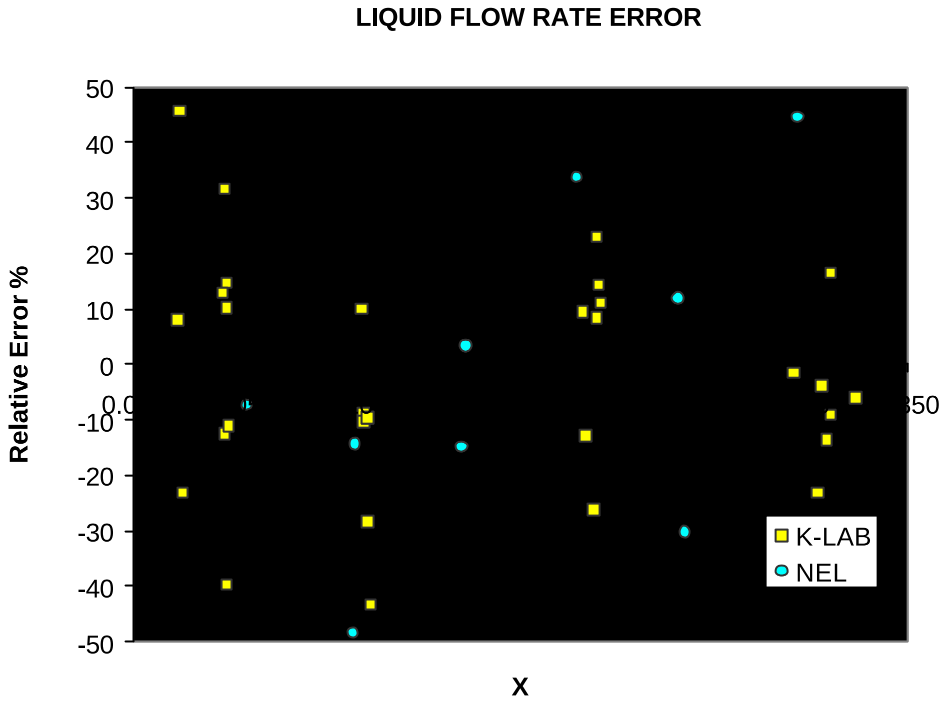


Figure 16: Liquid Flow Rate Relative Error vs. Lockhart-Martinelli Parameter (K-Labs+NEL General Model)

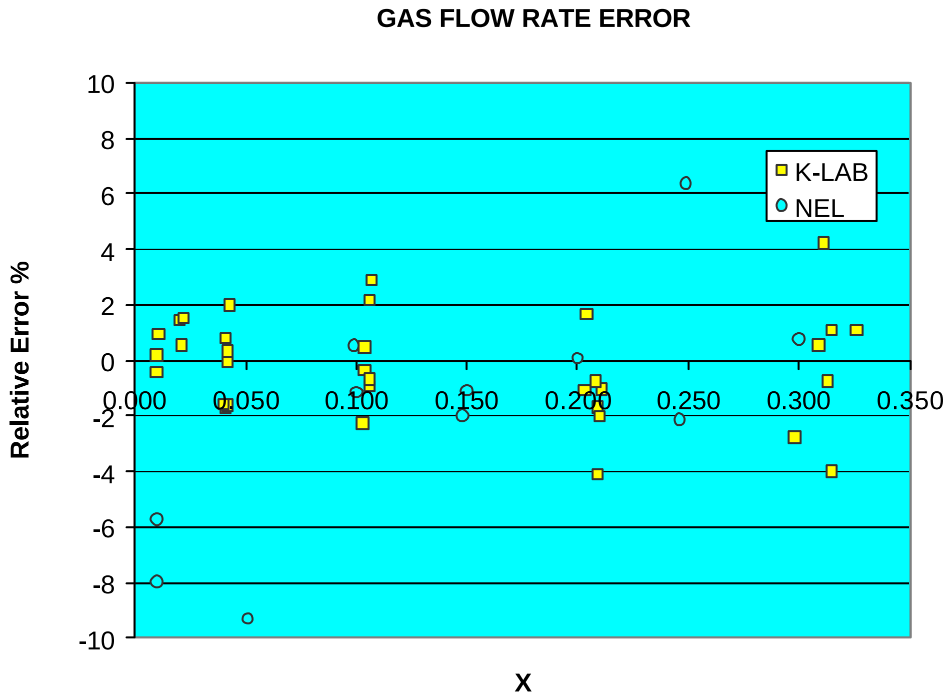


Figure 17. Gas Flow Rate Relative Error vs. Lockhart-Martinelli Parameter (K-Labs+NEL General Model)

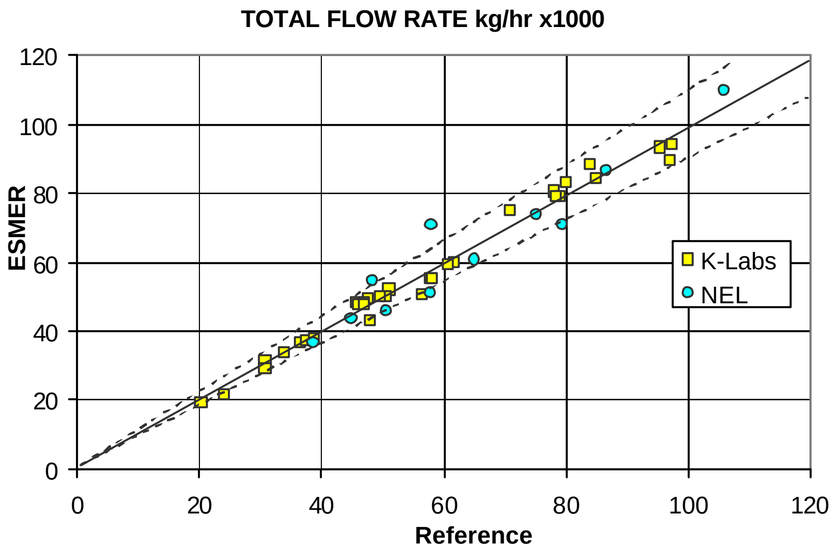


Figure 18. Total Mass Flow Rate vs Reference (K-Labs+NEL General Model)

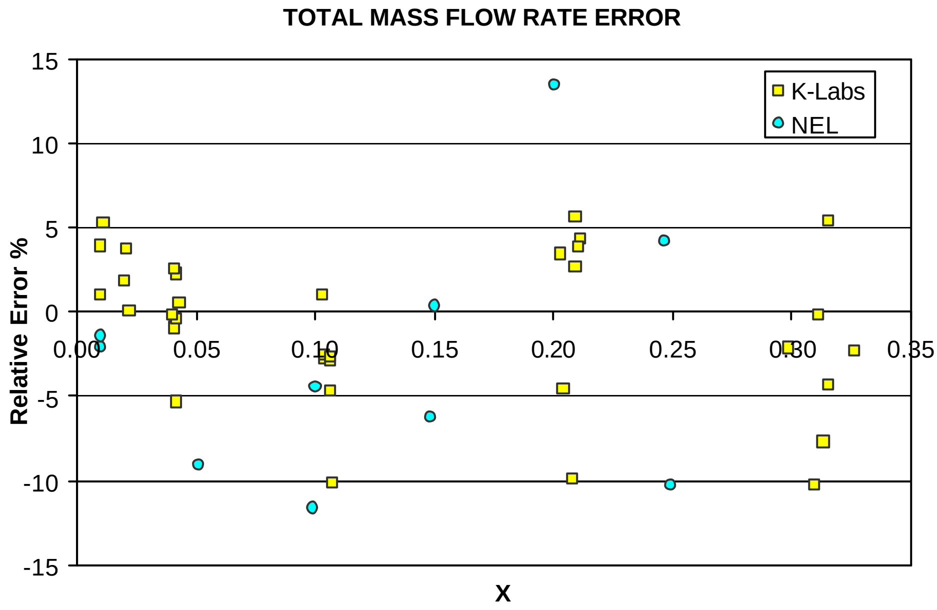


Figure 19. Total Mass Flow Rate Relative Error vs. Lockhart-Martinelli Parameter (K-Labs+NEL General Model)

References

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Acknowledgment

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