Back-Up Paper

Uncertainty Based Production Allocation Using Virtual Multiphase Flow Metering

Hallgeir Melbø, Bjørn Bringedal, Nicolas Alexander Hall,
Svein Arne Morud, Egil Birkemoe and Callum Smyth
ABB AS

North Sea Flow Measurement Workshop
26-29 October 2004

UNCERTAINTY BASED PRODUCTION ALLOCATION USING VIRTUAL MULTIPHASE FLOW METERING

Hallgeir Melbø, ABB AS, Corporate Research Center
Bjørn Bringedal, ABB AS, Enhanced Oil Production
Nicolas Alexander Hall, ABB AS, Enhanced Oil Production
Svein Arne Morud, ABB AS, Corporate Research Center
Egil Birkemoe, ABB AS, Enhanced Oil Production
Callum Smyth, A/S Norske Shell

---

1 ABSTRACT

This article addresses the problem of allocating rates back to individual wells. Handling uncertainty during production allocation is a well-known problem, and API (American Petroleum Institute) has recently recommended a practice (API-RP85) for handling it, see [1]. However, the recommendation is not necessarily the best choice of method when the meter measuring the total flow is a flow meter with far from fiscal accuracy, in which case the purpose of the allocation typically is reservoir management and well diagnostics rather than a splitting of the revenue from the exported fluids. A typical example of this is allocation of produced water back to the wells. We derive a method for estimating statistically optimal estimators for the rates produced by the individual wells in the case where a flow meter measures the total produced fluid, possibly over time, with a given accuracy. The estimates are based on estimated (or measured) rates from the individual wells, which are computed from parameters that contain uncertainty. The parameter uncertainties are applied to estimate the uncertainty in each rate. The estimated rates, their standard deviations, and the master measurement measuring the total flow are finally used to compute the most likely rates produced from each well at each point in time. Directly from the method the uncertainty in the allocated rates can also be computed.

The article consists of a detailed theory part that describes the suggested method and an example that shows how it can be applied. The example is taken from the Draugen oil production platform, which is operated by Shell and located in the North Sea. There the virtual multiphase flow meter Well Monitoring System [2], [3] is installed and provides the necessary rate estimates and sensitivity analysis that is required in our approach.

2 INTRODUCTION

The question of how to allocate produced rates to individual wells is old. However, the industry is moving into a new era for measurement and allocation where the old assumptions no longer hold true, and traditional allocation techniques cannot accommodate the realities of multiphase measurement [4]. In fact, the allocation problem is not only one, but rather two problems. One is to allocate a fixed amount of produced fluids to each of the wells such that the sum of all well rates equals the fixed total amount. This is typically of interest when there is a requirement that the well rates add up to e.g. a fiscal measurement. A different but related problem is to find the best estimate for the rates coming from each well aided by a flow meter which measures the total produced fluids, taking into account that the flow meter is not exact. This is very much of interest for instance when allocating the total produced water to each well for the purpose of reservoir management and well diagnostics. API-RP85 covers the first problem, so we will only be addressing the latter of these problems here.

The starting point for our allocation algorithm is to have available rate estimates for all the wells at all relevant points in time. The rate estimates may come from flow meters, virtual flow meters or any other rate estimation technique. To perform optimal allocation of rates one also needs to have estimates for the uncertainty in the measured or estimated rates. In a later section we will show how this can be done when the rate estimates are based on parameters that contain uncertainty.

3 THEORY

3.1 Estimating most likely rates allowing for uncertainty in master meter

The allocated rates that we are seeking in this article will be based on statistical estimates. The estimated rates from each well for each timestep will be treated as statistical events with a known uncertainty. Very often the uncertainties are actually not known, but we will get back to how they can be estimated. Our strategy is to look for the most likely expected values for the rates, which are the best estimate for the true rate from each well for each timestep. We also allow for uncertainty in the master meter, which means the optimal estimates of rates from the wells will not in general add up to the master measurement, but rather to the statistically most probable reading at the master meter level, i.e. the best estimate for the expected value of the master meter. In this context the term "master meter" should only be understood as the meter measuring the total flow, and not necessarily a meter of very high accuracy.

Let N_w be the number of wells and let N_t be the number of times the rate from each well has been estimated during the time period ΔT. The oil produced during this time is what has been measured by the master meter. Note that it will clearly be seen how to treat the estimation also when measurements of the total flow take place on a continuous basis, e.g. if the master meter is located on a flowline common to all the wells. Furthermore, let q_{ij} be the estimated (or measured) rate produced from well i in timestep j , where timestep j has length Δt_j .This gives the relation

$$\Delta T = \sum_{j=1}^{N_t} \Delta t_j .$$

Denote by v_M the reading of the master meter for the total production over the time period $\Delta T.$ Define μ_{ij} and σ_{ij} to be the expected value and standard deviation corresponding to q_{ij} and let μ_v and σ_v be the standard deviation of the measurement v_M.

Throughout this article we will assume that the estimated rates are random variables distributed according to normal distributions, i.e. their probability density functions are of the following form,

$$f(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} ,$$

where x is the value of a stochastic variable $X,$ and μ and σ are its expected value and standard deviation.

Assuming now that the estimates for rates are independent stochastic variables, the probability of estimating what has actually been estimated (or rather the joint probability density function for all the stochastic rates), given a set of expected values, is nothing but the product of all density functions. It can therefore be written as

$$\begin{aligned}\tilde{F} &= f(v_M;\mu_v,\sigma_v)\cdot \prod_{i=1}^{N_w}\prod_{j=1}^{N_t} f(q_{ij}\Delta t_j;\mu_{ij}\Delta t_j,\sigma_{ij}\Delta t_j) \\ &= \frac{1}{\sqrt{2\pi}\sigma_v} e^{-\frac{1}{2}\left(\frac{v_M-\mu_v}{\sigma_v}\right)^2} \prod_{i=1}^{N_w}\prod_{j=1}^{N_t} \frac{1}{\sqrt{2\pi}\sigma_{ij}\Delta t_j} e^{-\frac{1}{2}\left(\frac{q_{ij}-\mu_{ij}}{\sigma_{ij}}\right)^2} ,\end{aligned}$$

where we have used the fact that for a stochastic variable X multiplied by a scalar Δt we have

$$E(X\,\Delta t) = \mu\,\Delta t \quad \text{and} \quad Var(X\,\Delta t) = \sigma^2 \Delta t^2,$$

in which μ and σ are the mean and standard deviation of X. Note that the assumption regarding the variables being independent may not apply in all cases. This can typically be the situation if several wells are gathered into one flowline and information along the flowline is used to estimate the rates. However, in many cases the assumption may be a feasible approximation.

We will now determine the best estimate for the expected values, μ_{ij}, by requiring them to be the set of variables that maximise the joint probability density function $\tilde{F}$. They are therefore known as maximum likelihood estimators. Since the logarithm is a monotone function of its argument we define F to be

$$F = \ln \tilde{F}\,.$$

Hence F can be considered instead of $\tilde{F}$ to identify the parameters that give the maximum value. As already mentioned, we assume that the estimated rates are distributed according to normal distributions, in which the true rates are the expected values. For the true rates it holds that the integral of the rates equals the total volume at the master meter level. As the true rates are represented by the expected value of each of the distributions we require the corresponding relation to hold holds also for the expected values, i.e.

$$\mu_V = \sum_{i=1}^{N_w}\sum_{j=1}^{N_t} \mu_{ij}\Delta t_j\ . \tag{1}$$

Enforcing this condition we obtain

$$F = \ln\left(\frac{1}{\sqrt{2\pi}\sigma_V}\right) - \frac{1}{2}\left(\frac{V_M - \sum_{i=1}^{N_w}\sum_{j=1}^{N_t}\mu_{ij}\Delta t_j}{\sigma_V}\right)^2$$

$$+\sum_{i=1}^{N_w}\sum_{j=1}^{N_t}\ln\left(\frac{1}{\sqrt{2\pi}\sigma_{ij}\Delta t_j}\right) - \sum_{i=1}^{N_w}\sum_{j=1}^{N_t}\frac{1}{2}\left(\frac{q_{ij}-\mu_{ij}}{\sigma_{ij}}\right)^2 \quad .$$

To find the maximum of this function we simply require all partial derivatives of F to vanish, i.e.

$$\nabla_\mu F = 0 \quad ,$$

in which ∇_μ denotes the differentiation operator with respect to each of the expected values. Hence, this is a vector equation with N_w*N_t equations in total. The function can easily be differentiated,

$$\frac{\partial F}{\partial \mu_{ij}} = \frac{q_{ij}-\mu_{ij}}{\sigma_{ij}^2} + \frac{\left(V_M - \sum_{k=1}^{N_w}\sum_{r=1}^{N_t}\mu_{kr}\Delta t_r\right)\Delta t_j}{\sigma_V^2} \quad ,$$

and the line corresponding to the indices i,j in the equation becomes

$$\mu_{ij}\frac{\sigma_V^2}{\Delta t_j \sigma_{ij}^2} + \sum_{k=1}^{N_w}\sum_{r=1}^{N_t}\mu_{kr}\Delta t_r = V_M + q_{ij}\frac{\sigma_V^2}{\Delta t_j\sigma_{ij}^2} \quad . \tag{2}$$

This can be written as a matrix equation,

$$A_v \mu = b_v, \tag{3}$$

where

$$A_v = \begin{bmatrix} \frac{\sigma_v^2}{\Delta t_1 \sigma_{11}^2} + \Delta t_1 & \Delta t_1 & \cdots & \Delta t_{N_t} \\ \Delta t_1 & \frac{\sigma_v^2}{\Delta t_1 \sigma_{21}^2} + \Delta t_1 & \cdots & \Delta t_{N_t} \\ \vdots & & \ddots & \vdots \\ \Delta t_1 & \Delta t_1 & \cdots & \frac{\sigma_v^2}{\Delta t_{N_t} \sigma_{N_w N_t}^2} + \Delta t_{N_t} \end{bmatrix}, \qquad \mu = \begin{bmatrix} \mu_{11} \\ \mu_{21} \\ \vdots \\ \mu_{12} \\ \mu_{22} \\ \vdots \\ \mu_{N_w N_t} \end{bmatrix}$$

$$b_v = v_M \cdot \mathbf{1} + \begin{bmatrix} q_{11} \frac{\sigma_v^2}{\Delta t_1 \sigma_{11}^2} \\ q_{21} \frac{\sigma_v^2}{\Delta t_1 \sigma_{21}^2} \\ \vdots \\ q_{12} \frac{\sigma_v^2}{\Delta t_2 \sigma_{12}^2} \\ q_{22} \frac{\sigma_v^2}{\Delta t_2 \sigma_{22}^2} \\ \vdots \\ q_{N_w N_t} \frac{\sigma_v^2}{\Delta t_{N_t} \sigma_{N_w N_t}^2} \end{bmatrix}$$

in which **1** is the vector of all ones. Note that each line of the matrix A_v consists of first N_w entries involving Δt_1, corresponding to the first timestep for the N_w wells, thereafter N_w entries of Δt_2 , and so forth. The solution to the linear system is easily found as $\mu = A_v^{-1} b_v$. This gives the statistically optimal estimate for the rates from each individual well, and the optimal value for μ_v is found from equation (1).

3.2 Variance of allocated rates

The above shows that each entry in the solution vector, μ, is nothing but a linear combination of the events drawn from independent normal distributions: Each row of the inverse of the matrix A_v provides coefficients that are multiplied by each entry in the vector b_v which is the stochastic variable corresponding to v_M plus the stochastic variable corresponding to q_{ij} times a coefficient. The variance of the expected values for the rates can therefore be computed using the following relationship that holds for a stochastic variable Y which is the weighted sum of independent stochastic variables X_i,

$$Y = \sum_i k_i X_i \qquad \Rightarrow \qquad Var(Y) = \sum_i k_i^2 \, Var(X_i)\,. \tag{4}$$

Therefore, define D to be the matrix whose entries are the squares of the entries of the inverse of A_v, i.e.

$$d_{ij} = (a_{ij}^{-})^2\,,$$

where d_{ij} is an entry of D and a_{ij}^{-} is the corresponding entry of A^{-1}. Define the vector w as

$$w_k = \sigma_v^2 \quad + \quad \frac{\sigma_v^4}{\Delta t_j^2 \sigma_{ij}^2} \ .$$

Using these definitions, equation (4), and the relationship $\mu = A_v^{-1} b_v$, we obtain the relationship

$$Var(\mu) = Dw \ , \tag{5}$$

which expresses the variance of the expected values for the rates.

3.3 Simplified equations in case of continuous total measurements

In cases where the master meter operates continuously the linear system determining the expected values for the rates changes slightly. We do no longer take into account several time steps, so $N_t=1$ and we omit the indices referring to time. For simplicity, define the rate measured at the master meter as

$$q_M = v_M / \Delta t \, ,$$

and denote by μ_M and σ_M the expected value and the standard deviation of q_M, which makes

$$\mu_M = \sum_{i=1}^{N_w} \mu_i \qquad \text{and} \qquad \sigma_{\mathrm{M}} = \frac{\sigma_v}{\Delta t} \ . \tag{6}$$

Line i of the resulting linear system now reads

$$\mu_i \frac{\sigma_M^2}{\sigma_i^2} \quad + \quad \sum_{k=1}^{N_w} \mu_k \quad = \quad q_M \quad + \quad q_i \frac{\sigma_M^2}{\sigma_i^2} \quad .$$

Just as previously this can be solved as a linear system, but now the system can be solved by hand. Substitution easily verifies that the following value for μ_i satisfies the above equation,

$$\mu_i = q_i \quad + \quad \frac{\sigma_i^2}{\sigma_M^2 + \sum_{k=1}^{N_w} \sigma_k^2} \left(q_M - \sum_{k=1}^{N_w} q_k \right) \ . \tag{7}$$

From this and equation (6) we also directly obtain

$$\mu_M = q_M \quad - \quad \frac{\sigma_M^2}{\sigma_M^2 + \sum_{k=1}^{N_w} \sigma_k^2} \left(q_M - \sum_{k=1}^{N_w} q_k \right) \ . \tag{8}$$

As previously shown for the full system over several timesteps, the variances of μ_i and μ_M are found from equation (4) as

$$\begin{aligned} Var(\mu_i) &= \sigma_i^2 \left(1 - \frac{\sigma_i^2}{\sigma_M^2 + \sum_{k=1}^{N_w} \sigma_k^2} \right)^2 \quad + \quad \frac{\sigma_i^4}{\left(\sigma_M^2 + \sum_{k=1}^{N_w} \sigma_k^2 \right)^2} \left(\sigma_M^2 + \sum_{\substack{k=1 \\ k \neq i}}^{N_w} \sigma_k^2 \right) \\ Var(\mu_M) &= \sigma_M^2 \left(1 - \frac{\sigma_M^2}{\sigma_M^2 + \sum_{k=1}^{N_w} \sigma_k^2} \right)^2 \quad + \quad \frac{\sigma_M^4 \sum_{k=1}^{N_w} \sigma_k^2}{\left(\sigma_M^2 + \sum_{k=1}^{N_w} \sigma_k^2 \right)^2} \ . \end{aligned} \tag{9}$$

It is interesting to note that there is a strong connection between the optimal values for μ_i and μ_M found here and the values suggested by API. The expected values μ_i and μ_M can be viewed as adjusted values for q_i and q_M, and here we allow for both q_i and q_M to be adjusted whereas API only allows for adjustments made to q_M. However, the allocation method recommended by API reads

$$q_i^{adjusted} = q_i \quad + \quad \left(\frac{\sigma_i^2}{\sigma_M^2 + \sum_{k=1}^{N_w} \sigma_k^2} + \frac{\sigma_M^2}{\sigma_M^2 + \sum_{k=1}^{N_w} \sigma_k^2} \cdot \frac{q_i}{\sum_{k=1}^{N_w} q_k} \right) \left(q_M - \sum_{k=1}^{N_w} q_k \right).$$

This is exactly the same adjustment as is made in our analysis, except that the adjustment that was assigned to the master meter in our analysis is spread out across the wells according to their relative production rates. That means, if we sum up the second term in the API adjustment we get exactly the adjustment we assign to the master meter in our analysis, except for the sign. The signs come out as opposite because after having been adjusted the master meter and the well estimates meet somewhere in between the master meter reading and the sum of the well estimates. If for instance the master meter has a higher reading than the sum of well rates the well rate adjustments are positive and the master meter adjustment is negative. Thereby, if no adjustment is made to the master meter (as in the API recommendation), a *larger* adjustment needs to be made to the well rates.

3.4 Estimating the variance for each rate

In this section we will address the question of how to estimate the variance in each estimated rate. The basic assumption in our approach is that close to the true rates each rate estimate can be well approximated by a linear model in which the (independent) variables have known uncertainties. The rate estimates are typically based on models that use uncertain parameters and measurements, e.g. a pressure measurement. In this case the assumption would be that in a small region the estimated rate depends linearly on this pressure measurement and the measurement has a known uncertainty. The uncertainty in the parameters will be taken as a constant, η, times their standard deviations, and it is assumed that the user defined confidence intervals (defined by the constant) are the same for all parameters, e.g. a 95% confidence interval, which means that the constant η is the same for all uncertain parameters and measurements. We also assume that the models are well tuned and without systematic errors, such that the errors are random variables, not biased towards either side.

Below we will be using the following definitions

Q	= a rate
β	= the vector of uncertain parameters that take part in the estimate of Q
β^0	= the values of β used in the original estimate for Q
s_i	= the standard deviation for β_i
ηs_i	= user specified uncertainty for β_i, half the width of the confidence interval of β_i

The linear model for the estimated rate, $Q=Q(\beta)$, can now be formed in the following way,

$$\begin{aligned} Q &\approx Q\left(\beta^0\right) + \sum_i \left.\frac{\partial Q}{\partial \beta_i}\right|_{\beta=\beta^0} (\beta_i - \beta_i^0) \\ &= k^0 + \sum_i \left.\frac{\partial Q}{\partial \beta_i}\right|_{\beta=\beta^0} \beta_i \quad , \end{aligned}$$

where k^0 is a constant. The parameters are assumed to be independent stochastic variables, so according to equation (4), the variance of Q is now

$$Var(Q) \approx \sum_i \left(\frac{\partial Q}{\partial \beta_i}\bigg|_{\beta=\beta^0} \right)^2 Var(\beta_i)\,.$$

The derivatives in the above expression can be approximated by aid of estimates of the rates found with perturbed values for the β_i's. Defining e_i to be the unit vector in the i'th direction the approximation may be done in the standard way as follows:

$$\frac{\partial Q}{\partial \beta_i}\bigg|_{\beta=\beta^0} \approx \frac{\Delta_i(Q)}{\eta s_i}\,,$$

where

$$\Delta_i(Q) = Q(\beta^0 + e_i \eta s_i) \quad - \quad Q(\beta^0)\,.$$

From the approximation of the derivatives and the expression for the variance we obtain

$$\begin{aligned} Var(Q) &\approx \sum_i \frac{\left(\Delta_i(Q)\right)^2}{\eta^2 s_i^2} s_i^2 \\ &= \frac{1}{\eta^2} \sum_i \left(\Delta_i(Q)\right)^2\,. \end{aligned} \tag{10}$$

4 EXAMPLE

The example is taken from the oil production platform Draugen, which is operated by Shell and located in the North Sea. At Draugen 6 platform wells enter the separators and there is a continuous rate measurement of the total flow of oil, gas, and water. The measurements are not for fiscal purposes. The meter measuring the total flow is assumed to have 3% uncertainty. Since the continuous total rates are available, we use the simplified system of equations described in Section 3.3.

At Draugen the software package Well Monitoring System, which is an online system for steady state multiphase flow simulation and rate estimation in networks, estimates the oil, gas, and water rates from each well on a regular basis (Δt in the order of minutes). We have picked out one point in time in a period when the plant was at steady state, and with the data from that time we have performed the allocation based on equations (7) and (8). The analysis was carried out for the oil and the water rates.

The first step in the algorithm is to decide on uncertain parameters with corresponding confidence intervals, and to perform the perturbed rate estimates. The perturbed results are used to determine the variance in the rates according to equation (10). The chosen uncertain parameters and the corresponding (guessed) 95% confidence intervals are shown in Table 1. The chosen uncertainties are probably larger than what is realistic in a tuned model, but the results show that the estimates are quite robust towards uncertainties in the parameters. Furthermore, all the wells have been treated uniformly to keep the example simple, although variations in parameter uncertainty between the wells is quite likely. The chosen width of the confidence interval (95%) implies

$$\eta \approx 2\,.$$

The metered oil and water rates (=$Q(\beta^0)$ for oil and water), their estimated standard deviations and the differences between metered and allocated rates for each well are found in Table 2. Note that we have used 5 as a lower limit on standard deviation.

For the allocated rates we have also computed the standard deviation according to equation (9). The result is shown in Table 3, where the index θ is defined as

$$\theta = |q_i - \mu_i| \,/\, 2\sigma_i \quad .$$

If $\theta > 1$ there is reason to believe there are major uncertainties in the rate estimates that are not taken care of by the chosen set of uncertain parameters.

Table 1 - Uncertain parameters and definition of confidence intervals

Uncertain parameter (equal for all wells)	95% confidence interval
Gas-oil ratio	+/- 5%
Modelled static pressure differential in pipes	+/- 2%
Choke area	+/- 5%
Production index (near well area)	+/- 10%
Reservoir pressure	+/- 1 bar
Heat transfer coefficient in pipes	+/- 10%
Roughness of pipe walls	+/- 20%
Pressure measurement upstream of choke	+/- 0.2 bar
Pressure measurement downstream of choke	+/- 0.2 bar
Temperature measurement upstream of choke	+/- 0.5 K

Table 2 - Initial rate estimates with standard deviation and rate adjustments

	Oil			Water		
Well	**Metered rate**	**Std dev**	**Metered - allocated rate**	**Metered rate**	**Std dev**	**Metered - allocated rate**
1	2885	284	113	2293	145	92
2	5486	109	17	1371	27	3
3	3907	257	92	1232	149	97
4	1787	117	19	1192	80	28
5	6792	161	35	0	5	0.1
6	821	16	0.3	1232	23	2
Master meter	20856	626	-545	6912	207	-186

Table 3 - Allocation results and uncertainties

	Oil			Water		
Well	**Allocated rate**	**Std dev allocated rate**	***θ***	**Allocated rate**	**Std dev allocated rate**	***θ***
1	2772	264	0.20	2202	128	0.32
2	5469	108	0.08	1368	27	0.06
3	3815	242	0.18	1135	130	0.32
4	1767	115	0.08	1164	77	0.18
5	6756	156	0.11	0	5	0.01
6	821	16	0.01	1230	23	0.05
Master meter	21401	363	0.44	7098	153	0.45

It is clear from the tables that, as expected, the rates with the largest standard deviation get their allocated rates farthest away from the estimated ones to meet the requirements. Further, from the values of θ it is seen that all rates are well within their confidence intervals when centred at the estimated means. We also note that the standard deviations are smaller in the allocated rates than in the estimated (metered) rates, especially for the master meter. Finally, it is clear that the sum of the individual well rates are very close to the measured total flow, which indicates that the virtual flow meter, Well Monitoring System, is performing well.

5 SUMMARY AND CONCLUSION

We have proposed a method for allocating rates based on estimated well rates and measurements of the total flow. The user must specify the uncertain parameters entering the rate estimation formulas and the corresponding confidence intervals. Based on this input the algorithm returns the most likely rates, including uncertainties, produced from each well and for the total flow. The algorithm works when the measurement of the total flow is an online rate measurement and when the produced rates are stored in cells, in which case the measurement gives the total produced volume.

The example shows that the results are well in line with what is expected from the derivation of the methodology. It is worth noting that the current approach works equally well with any type of rate estimation technique as long as the sensitivity analysis required for estimating the variance for the rates can be performed.

6 ACKNOWLEDGEMENTS

The authors would like to thank the Shell Draugen team for allowing us to use rate estimates and measurements from the Draugen platform.

7 REFERENCES

[1] AMERICAN PETROLEUM INSTITUTE. Use of subsea wet-gas flowmeters in allocation measurement systems. API recommended practice 85, First edition, August 2003.

[2] R.VAN DER GEEST, W.H.BROMAN Jr., T.JOHNSON, R.H.FLEMING, and J.O. ALLEN. Reliability through data reconciliation. OTC 13000 (2001).

[3] H.MELBØ, S.A.MORUD, B.BRINGEDAL, R.VAN DER GEEST and K.STENERSEN. Software that enables flow metering of well rates with long tiebacks and with limited or inaccurate instrumentation. OTC 15363 (2003)

[4] R.A.WEBB. Allocation methods for commingled production using multiphase measurement – A future look at the Gulf of Mexico. Prepared for Multiphase Measurement users Roundtable. May 5th 2004.