Data reconciliation at the EO plant of Shell Nederland Chemie Moerdijk

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Report IWDE 93-11

Data Reconciliation at the EO Plant of
Shell Nederland Chemie Moerdijk

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December 1993

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Contents

1 Introduction

This report gives a summary of the results of a cooperation between the Moerdijk Managing Technology department of Shell Nederland Chemie and the Institute for Mathematics Consulting of the Eindhoven University of Technology (EUT). The purpose of this project is an investigation whether data reconciliation techniques could be of use in the EO plant of Shell Moerdijk. In the Appendix the original formulation of this feasibility study is given.

The main characteristics of the plant under consideration are:

a) the number of variables is very large

b) the balance equations are non-linear

c) both random and systematic errors are present.

In the field of data reconciliation numerous software packages are available [JMK]. However, these packages only apply to systems with linear balance equations and without systematic errors. Points b) and c) cause the present application to be a field of research. The project has been succesively carried out by four stagiaires supervised by TUE staff members. The work and the results have been extensively described in several reports [JvB, PR, RW, DJM]. The present report is meant to conclude the project and gives an overview of the mathematics and the results without going into details.

2 Problem description

The EO plant consists of a large number of process units, the core of which are two nearly identical reactors. Measurements of flow rates and concentrations of components are routinely made for the purpose of process control and process performance evaluation. When the process is in a steady state these measurements are expected to satisfy mass balances. These constraints are never satisfied exactly, because of the presence of random and, possibly, systematic (also called : gross) errors in the data. The latter errors may be due to, e.g., miscalibrated measuring instruments or unsuspected leaks. An additional difficulty is that not all variables are measured because of cost considerations or technical infeasibility.

The purpose of *data reconciliation* is to find estimates for:

a) the unmeasured variables

b) the true values of the measured variables

c) the systematic errors.

The information on which the estimation is based is twofold:

i) measured values of a subset of all variables

ii) the true values of all variables must satisfy the mass (and, possibly, energy) balance equations.

Detailed descriptions of the EO plant are given in [JvB, DJM]. To give an idea of the size of this system we mention that the total number of variables is 180, because there are 18 flows in each of which the flow rate and the concentrations of 9 components are of importance. The application of various straightforward assumptions reduces the number of variables to 98. Of these only 42 variables are measured. The number of mass balance equations is 74. These equations are non–linear in the variables containing, e.g., products of concentrations and flow rates.

3 Error modelling

The modelling of the errors is an essential ingredient of the data reconciliation procedure. This modelling follows from the physical principles of the measuring instruments. For the EO plant we found the following assumptions to be reliable:

- random errors are relative, i.e, proportional to the value of the measured variable

- systematic errors may have two components:

  1. a relative part
  2. an absolute part, leading to a constant shift (also called : bias)

So, for a particular measurement the model reads as

$$y = E_\alpha + E_\beta \eta + \varepsilon \eta$$

where

η	: true value of the measured variable
y	: measured value
E_α	: absolute part of the systematic error
E_β	: relative part of the systematic error
ε	: random error

The covariance matrix of the random errors is denoted by Σ. It is a diagonal matrix because the random errors are between different measurements.
One systematic error can be present in several measurements, because one measuring device may be used to measure a variable at different positions leading to correlated errors in these measurements.

4 Mathematical procedures

The idea behind data reconciliation is to adjust the measured values such that:

1. the corrected values satisfy the balance equations
2. the corrections or 'residuals' are as small as possible with respect to a (weighted) least squares norm.

4.1 Estimation of Σ

In the procedures dealt with hereafter the (diagonal) variance matrix Σ of the random errors is assumed to be known. The elements of Σ have been estimated from long series of data sets at successive time points. See [RW]. Plots of the measured values at successive time points reveal that in most time series definite trends are present indicating that the EO plant is not in a steady state when observed during a time window of days. It even turns out that sudden shocks appear at which nearly all variables jump to another value. The variance of the random error in a measurement can be calculated from the variance of the fast variations in the measurements. To that end the trend, i.e. the long–term variation, has to be removed. This has been done using the moving average technique meanwhile taking care of the sudden jumps in the signals. Because of these jumps it does not seem worth to apply a more sophisticated technique for trend removing.

4.2 Estimation of unmeasured variables

In [TM, JvB] it has been described how estimates for the unmeasured variables can be obtained from estimates for the true values of the measured variables via the so–called *projection method.* In general not all unmeasured variables can be estimated this way. However, in the EO plant the number and positions of measured variables turn out to be appropriate to obtain estimates for all unmeasured variables.
The projection method is applicable only in case of linear constraints. In the iterative approaches to be presented hereafter the non–linear constraints are linearized at each interation step. The projection method is then applied to the constraints in linearized form.

4.3 Random errors

If only random errors were present and if the balance equationse were linear, the problem could be solved as described in [TM]. To deal with the non–linearity an iterative procedure is introduced based on the Gauss–Newton method. See [JvB]. It consists of the following steps:

0. Find an initial guess for the values of all (measured and unmeasured) variables.
1. Linearize the balance equations around this working point.

2. Solve the resulting (linear) Gauss–Newton problem. This yields a direction vector along which the current estimates for the measured variables can be adjusted best.

3. Choose a step length following some (heuristic) algorithm and adjust the estimates for the measured variables.

4. Calculate new estimates for the unmeasured variables using the projection method.

Repeat the steps 1 – 4 around the new working point and keep iterating the process until convergence is reached. As shown in [JvB] this procedure works very well when applied to the EO plant. The number of iteration steps necessary to obtain a reasonably high accuracy is seldom more than 5.

4.4 Random and systematic errors.

If also systematic errors are present, the procedure in § 4.3 has to be extended. An important observation is that the systematic errors, i.e. the factors E_α and E_β in the model equations of the form given in § 3, are not present in the balance equations. This allows for a decoupling of the numerical estimation of random and systematic errors. Following this idea the following two steps are included into the procedure in § 4.3:

0′. Set initially $E_\alpha = 0$ and $E_\beta = 1$ for all systematic errors.

5. Estimate the systematic errors from the random error estimates obtained in step 4.

4.5 Instantaneous versus sequential

If the data reconciliation is based on a data set obtained at one time point, or within a very short time period, e.g., hourly averages, we call the procedure followed the *instantaneous approach*. If, however, data sets at successive time points are simultaneously used, we refer to it as the *sequential approach*.

4.5.1 Systematic errors in the instantaneous approach

In the instantaneous approach it is impossible to distinguish systematic from random errors, if the former are present in uncorrelated measurements. Only if one and the same systematic error influences more than one measurement, e.g., because the same measuring instrument is used, one can try to estimate systematic errors separately. In general, a systematic error can only be estimated in a reliable manner if this error is present in a lot of measurements. The smaller this number of measurements, the more unreliable the estimates are. To show this point an extreme case will be used as an example.

Example

Assume that one instrument is used to measure two variables. The measured values are y_1 and y_2. The estimates for the time values under the assumption of no systematic errors are η_1 and η_2 respectively. The pairs (y_1, η_1) and (y_2, η_2) are plotted in Fig. 1. If not any errors are present, these pairs lie on the diagonal $y = \eta$. If only random errors are present and lots of pairs (y_i, η_i) are available, the points scatter around the diagonal. If in addition a systematic error is present, the points scatter around another straight line, the position of which is determined by the values of the factors (E_α, E_β), that are to be estimated.

In this example we only have two pairs. Following the model in §3, these points have to satisfy, the equations

$$
\begin{aligned}
y_1 &= E_\alpha + E_\beta \eta_1 + \varepsilon_1 \eta_1 \\
y_2 &= E_\alpha + E_\beta \eta_2 + \varepsilon_2 \eta_2
\end{aligned}
$$

with $\varepsilon_1, \varepsilon_2$ the random errors.
If the points lie on the same side of the diagonal, as is the case in Fig. 1, one may interpret this as being caused by a systematic error, but it may also be just by chance. It is now to the user to decide which interpretation must be prefered. He might follow different strategies:

a. In view of the lack of information no conclusion about the systematic errors is drawn, setting $E_\alpha = 0$ and $E_\beta = 1$.

b. The absolute part is ignored setting $E_\alpha = 0$. The relative part E_β is then estimated from the slope of the straight line b in Fig. 1, which passes through the origin. The estimates η_1 and η_2 are accordingly be adjusted by projecting the points on line b.

c. One decides to estimate both E_α and E_β by ascribing all deviations from the diagonal to the systematic errors. This simply results in straight line c passing through both points. From its slope E_β is estimated and from its crossing of the vertical axis E_α is found. In this interpretation one has vanishing random errors: $\varepsilon_1 = \varepsilon_2 = 0$.

It will be clear that in cases b. and c. it is likely that the systematic errors are considerably overestimated. In the mathematical procedure described in § 4.4 and applied to the EO plant the same strategy as mentioned under c. is followed : possible trends in the residuals are as much as possible ascribed to systematic errors, irrespective of the number of the residuals involved. This implies that the instantaneous approach will tend to yield too large values for the systematic errors.

4.5.2 Systematic errors in the sequential approach

In the sequential approach one obtains for each measurement y_t on time t an estimate η_t. A possible systematic error can be estimated from as many pairs (y_t, η_t) as there are successive data sets. So, if enough data sets are available, the disadvantages discussed in §4.5.2 are not present. E.g., even a systematic error figuring in only one measurement (and not in a couple of correlated measurements) can be detected this way.

4.6 The residual approach

In addition to the instantaneous and sequential approaches we mention the *residual approach.* This method is conceptually simpler than the other ones. In the residual approach the instantaneous approach is applied to successive data sets ignoring in the first instance systematic errors. So one sets $E_\alpha = 0$ and $E_\beta = 1$ for all measurements. Then, the residuals at successive times are analyzed. If the residual of a specific measurement appears to be not normally distributed, but shows a trend over time, one concludes to a systematic error in that measurement. Theoretically this procedure is not fully sound, because the instantaneous approach, assuming only random errors, is apparently not applicable in those cases, but the method is applied in the EO plant with some succes.

5 Results and discussions

In [JvB, PR] the instantaneous approach has been applied to a data set from 26–02–91. In [DJM] all approaches mentioned in §4 have been applied to successive data sets from 17 and 18–05–93. Here, we give a concise overview of all the results.

5.1 Estimation of Σ

In [RW] several methods to estimate the (diagonal) matrix Σ containing the variances of the random errors are discussed. An appropriate method is to make use of long time series of successive measured values. The long–term trends in these series, due to the system not being in a steady state, are removed via the *weighted moving average* technique. The variances of the remaining residuals are estimates for the diagonal elements of Σ. Two points should be special care taken of:

- The window length must be chosen such that the residuals are normally distributed. A length of 18 for a series of 2 minutes data turns out to be satisfactory.
- The time series show sudden jumps. These can be best removed by hand.

5.2 Estimation of only random errors

With $E_\alpha = 0$ and $E_\beta = 1$ for each measurement only random errors are estimated. The iterative process described in §4*c* converges rapidly and yields estimates for all measured and nearly all unmeasured variables. Furthermore, in [DJM] it is found that the instantaneous and sequential approaches yield nearly identical results. So, we conclude that the information in one data set is enough to obtain reliable estimates for the random errors via the instantaneous method, provided that no systematic errors are present. If this would be the case in the MEOD plant, the residuals would scatter in a random way. However, for some variables they show definite biases over time . In the residual approach these biases are used as indications for systematic errors.

5.3 Estimation of random and systematic errors

In [PR] it is shown by introducing artificial errors in the real data set that big systematic errors (in the order of about 30 %) in mass flow measurements are detectable using the instantaneous method. However, in the real data the systematic errors, if any, are apparently much smaller than those used in these simulations, and the instantaneous method did not detect any systematic error in the EO data.

In [DJM] the residual and sequential methods are applied and we shortly discuss the main results. It should be emphasized that these results have been calculated *without* using the knowledge that some of the systematic errors are in fact identical because the same measuring device is used for a couple of measurements.

0_2 flow into $M101$

A systematic error in the 0_2 concentration of the flow into the mixer $M101$ can in principle not be estimated with the instantaneous approach, because not enough balance equations are available. The software then automatically sets $E_\alpha = 0$ and $E_\beta = 1$ for this variable and the instantaneous approach, applied successively, reduces to the residual approach. In Fig. 1.03, quoted from [DJM], the estimates are a small but systematic amount above the measured values, leading in the residual approach to the estimate $E_\beta = 0.99$. The sequential approach, in which E_β is estimated directly, yields $E_\beta = 0.95$. The latter estimate is the most reliable one from a theoretical point of view. We conclude that the residual approach may be useful to indicate the presence of a systematic eror, but it underestimates its absolute value highly.

Total mass flow into $R101a$

In Fig. 1.07, quoted from [DJM], results for the mass flow into the reactor are given. For this variable a possible systematic error can be in principle be found from the instantaneous approach leading to the estimate $E_\beta = 0.96$ (setting $E_\alpha = 0$). The sequential approach yields $E_\beta = 0.98$. In accordance with the considerations in §4 the instantaneous method overestimates the systematic error if this figures in only a few balance equations.

Selectivity

Figures A1.01 and B1.01 show the estimated selectivities for the two reactors from the instantaneous and sequential approach respectively. Both methods yield very similar selectivity curves. The amplitudes of the variations are smaller for the sequential approach, but still larger than expected from physical considerations about the stability of the system. One reason, but certainly not he only one (see below) , might be that the series of data sets used is far from being ideal. Around 3 pm the 17^{th} July and 5 pm the 18^{th} July the data show sudden jumps as if either the system or the recording software experienced sudden shocks. At those time points the instantaneous method did not converge. Around these points the estimated selectivities show definite dips and peaks. It is to be expected that the sequential approach will yield less varying estimates when data sets without such shocks are used.

Summary of systematic errors

In table A4.2 the estimates for all possible systematic errors are given as obtained with the sequential approach. These results should be interpreted with reserve, because no systematic investigation is yet performed and the present estimates are based on only one series of data sets. In Table A4.2 95% confidence limits are given. The interpretation is that, with 95% confidence, the estimates for the systematic errors are between the values given in the columns under the headings 'lower conf' and 'upper conf'. If such an interval does not include the orirgin, it is concluded that a systematic error is present (see last column). In 24 measurements such significant errors are detected. Most of them are very small. The bigger ones are in the total mass flows (about $\pm 7\%$).

In table A4.3 a subset of these results is ordened otherwise. There the systematic errors that should be the same are mentioned together. It is seen that equality is indeed found for measurements in flows at the same side of the reactors, i.e. streams 3 and 4 (inlets) and streams 5 and 6 (outlets).. This is more or less trivial, because there the flows are merely splitted or combined. Estimates at different sides of the reactors show differences. In general the agreement is good, but in some cases the corresponding confidence intervals have no overlap. Although this can partly be understood from the way the data are obtained, it seems that at this point the results are somewhat inconsistent.

There are three possible reasons for these findings. First, in these calculations the assumption $E_\alpha = 0$ is used. If these systematic errors indeed have an additional component, simultaneous estimation of both E_α and E_β might improve the consistency of the results. Second, it might be the case that the number of measurements and/or balance equations used is indeed too small. This could be easily improved by putting into the balance equations the information that certain subsets of measurements must have identical E_α and E_β factors. This has the extra advantage that it reduces the number of variables to be estimated considerably. Third, it has been observed independently that some systematic errors are time dependent and vary even on a scale of hours, possibly because of correlation with the weather conditions. The sequential approach is based on the assumption of time independent systematic errors, so this aspect might slightly corrupt the estimates.

6 Conclusions and recommendations

The project has led to a number of *conclusions* summarized hereafter. For all the methods mentioned software have been developed in MATLAB. Only research versions of the programs are available. These are computationally efficient, but not yet user-friendly.

1. The Σ matrix containing the variances of the random errors can quite easily be estimated from successive data sets.

2. The instantaneous approach is

   - very appropriate to detect random errors if no systematic errors are present. The present number of measurements (42) is large enough to obtain estimates for nearly all (measured and unmeasured) variables in the MEOD plant.
   - not much appropriate to estimate systematic errors. Some possible systematic errors can not be estimated because they do not figure in enough balance equations. If systematic errors can be estimated, this approach tends to overestimate the values.

3. The residual approach is conveniently applicable, but tends to underestimate possible sustematic errors.

4. The sequential approach is highly appropriate for the simultaneous estimation of random and systematic errors provided that

   - successive data sets are available preferably from a period in which the plant operates smoothly, i.e. without sudden jumps in the data.
   - as many information as available is included into the balance equations (e.g. the information that certain systematic errors are identical).

These insights lead to the following *recommendations*:

a) Use the sequential approach because in the MEOD plant systematic errors are present.

b) Use a great number of successive data sets, but make sure that in the period under consideration the system did not undergo sudden shocks.

c) Use as many information in the balance equations as available. E.g., include the knowledge that some systematic errors occur in more measurements. A lot of extra information can also be derived from inclusion of the energy balances.

d) Estimate not only the multiplicative component E_β in the systematic errors, but also the additive one E_α.

e) Check the method carefully by applying it shortly before and shortly after a recalibration of a number of measuring instruments. The improvements made should be immediately found back in the reconciliation results.

f) Develop a full-proof and user-friendly environment for the reconciliation programs. Special attention should be paid to a smooth data transfer from the computer monitoring the EO system to the reconciliation package, and to an appropriate (graphical) presentation of the results.

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Appendix : projektformulering (juli 1991)

Datavereffening en Gross-errordetektie in de Ethyleenoxide fabriek van Shell Nederland Chemie B.V., Moerdijk.

In de procesindustrie is het van groot technisch en economisch belang de diverse massastromen onder kontrole te hebben. Men plaatst daarom op geëigende plaatsen in het systeem flowmeters. Bij de interpretatie van de meetgegevens kunnen zich enkele complicaties voor doen:

a) Niet alle massastromen kunnen gemeten worden.
b) De meetgegevens bevatten random meetfouten.
c) De flowmeters kunnen een systematische fout hebben.
d) Er kan ergens een lek opgetreden zijn.

Verschijnselen c) en d) vat men in de literatuur samen onder de term "gross errors".

De meetgegevens worden voor twee doelen gebruikt:

1. **Datavereffening**: Schat uit de gemeten waarden de exakte flowgegevens (zowel gemeten als niet-gemeten).
2. **Foutdetektie**: Schat of er gross errors opgetreden zijn en waar deze zich in het systeem bevinden.

Deze facetten kunnen niet onafhankelijk van elkaar behandeld worden. We zullen de te gebruiken technieken kort toelichten en vervolgens enige opmerkingen plaatsen.

Bij het toepassen van datavereffening spelen de (bekend veronderstelde) massa- en energiebalansen een centrale rol. Deze balansen geven (vaak lineaire) relaties tussen de concentraties op verschillende plaatsen van de bij het proces betrokken componenten. Meestal worden niet alle flows op alle meetpunten bepaald. In dat geval dienen de balansen gereduceerd te worden met een techniek beschreven in bijv. [1]. Deze reductieprocedure is niet uniek en er dient te worden nagegaan hoe de gemaakte keuze van invloed is op de berekeningen. De niet-gemeten flows zijn alleen te schatten indien ze geen gesloten loop in het systeem vormen.
De gemeten flows zullen in het algemeen niet precies voldoen aan de (gereduceerde) balansen tengevolge van de boven genoemde fouten b), c) en d). Indien er alleen random meetfouten zijn en geen systematische afwijkingen of lekken, is het probleem van datavereffening theoretisch opgelost [1 - 8]. De oplossing is gegeven in termen van de covariantiematrix van de random meetfouten. Het schatten van deze matrix kan bemoeilijkt worden door niet-stationariteit van het proces en correlaties tussen de random meetfouten van opeenvolgende metingen. In dat geval dienen de trends uit de gemeten tijdreeksen gefilterd te worden. In [9] staan hiervoor geschikte technieken beschreven, waarbij gebruik gemaakt wordt van het Kalman filter en ARMA modellen.

In de Ethyleenoxide fabriek treden met vrij grote zekerheid wél systematische fouten op. Voor het schatten van deze fouten is in de literatuur een scala van methoden bekend. Sommige daarvan zijn globaal en geven (met zekere kans) aan of er ergens een gross-error is opgetreden. Andere, meer verfijnde technieken zijn gebaseerd op analyse van de lokale residuen, die verkregen zijn door bij het datavereffenen systematisch sets van metingen weg te laten. In [2] wordt hiervoor een efficiënte methode beschreven. In [7] worden verschillende methoden vergeleken. Alle methoden veronderstellen dat de covariantiematrix van de random meetfouten bekend is. De schatting van deze matrix uit de data kan een fout bevatten ten gevolge van de aanwezigheid van gross-errors. Dit probleem zal aangepakt worden via een iteratieve procedure. Men gaat daarbij uit van een ruwe schatting voor de verdeling van de gross-errors (bijvoorbeeld helemaal geen gross-errors). Vervolgens worden de data hiervoor gecorrigeerd en wordt de benodigde covariantiematrix geschat uit de data, Daarna voert men een geschikte test op gross-errors uit. Dit levert een nieuwe schatting voor de gross-errorverdeling op en daarmee wordt de cyclus herhaald totdat convergentie bereikt is. Het opstellen van de criteria voor convergentie is een belangrijk onderdeel van het projekt.

Opmerking 1.

Het projekt heeft een aantal researchmatige aspekten. Weliswaar zijn uit de literatuur methoden te halen om datavereffening en gross-errordetektie separaat uit te voeren, doch met de toepassing op de boven beschreven iteratieve manier is niet veel ervaring opgedaan. Het projekt dient opgevat te worden als een feasibilitystudy naar de mogelijkheid om deze technieken toe te passen op de Ethyleenoxidefabriek. Daartoe zal er software ontwikkeld worden binnen het IWDE, waarmee karakteristieke meetgegevens, beschikbaar gesteld door Shell Nederland Chemie B.V., Moerdijk, geanalyseerd zullen worden.
Na afloop van het projekt zal deze software overgedragen worden aan de contactpersoon namens Shell. Echter, het is niet de bedoeling dat deze software in een vorm gegoten wordt, die deze geschikt zou maken voor gebruik door niet-specialisten.

Opmerking 2.

Binnen het projekt zal ook nagegaan worden of er onderscheid gemaakt kan worden tussen systematische fouten in de flowmeters en lekken. Het is bij voorbaat niet duidelijk of deze verfijning praktisch haalbaar is. In theorie lijkt dit onderscheid wel te detekteren te zijn, indien er een overmaat aan data voor handen is.

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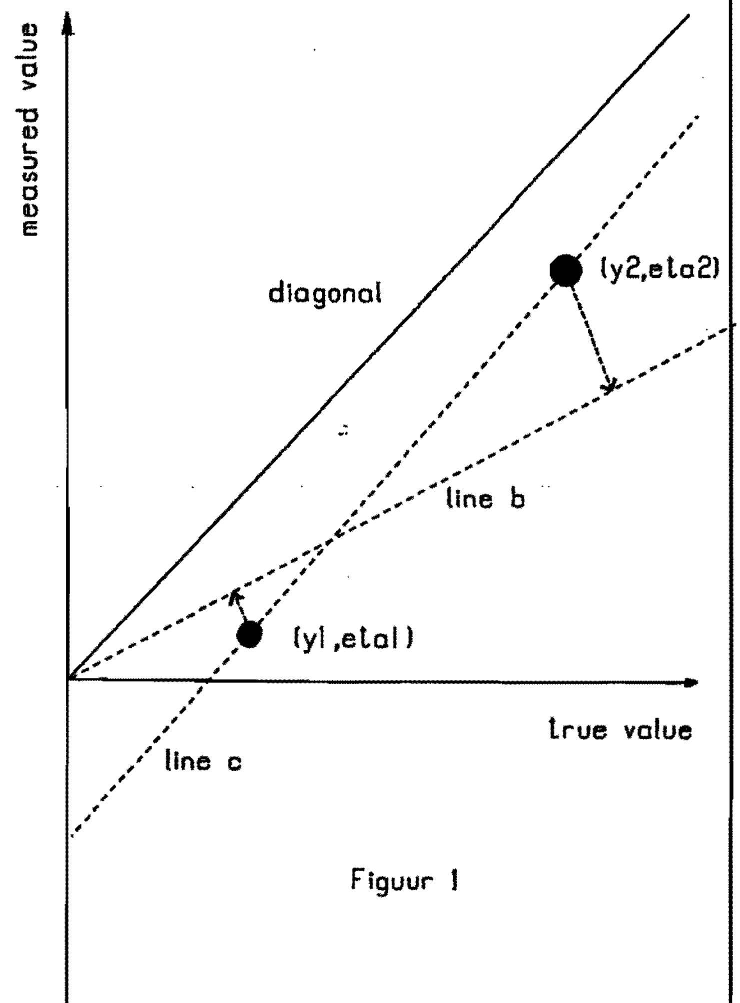
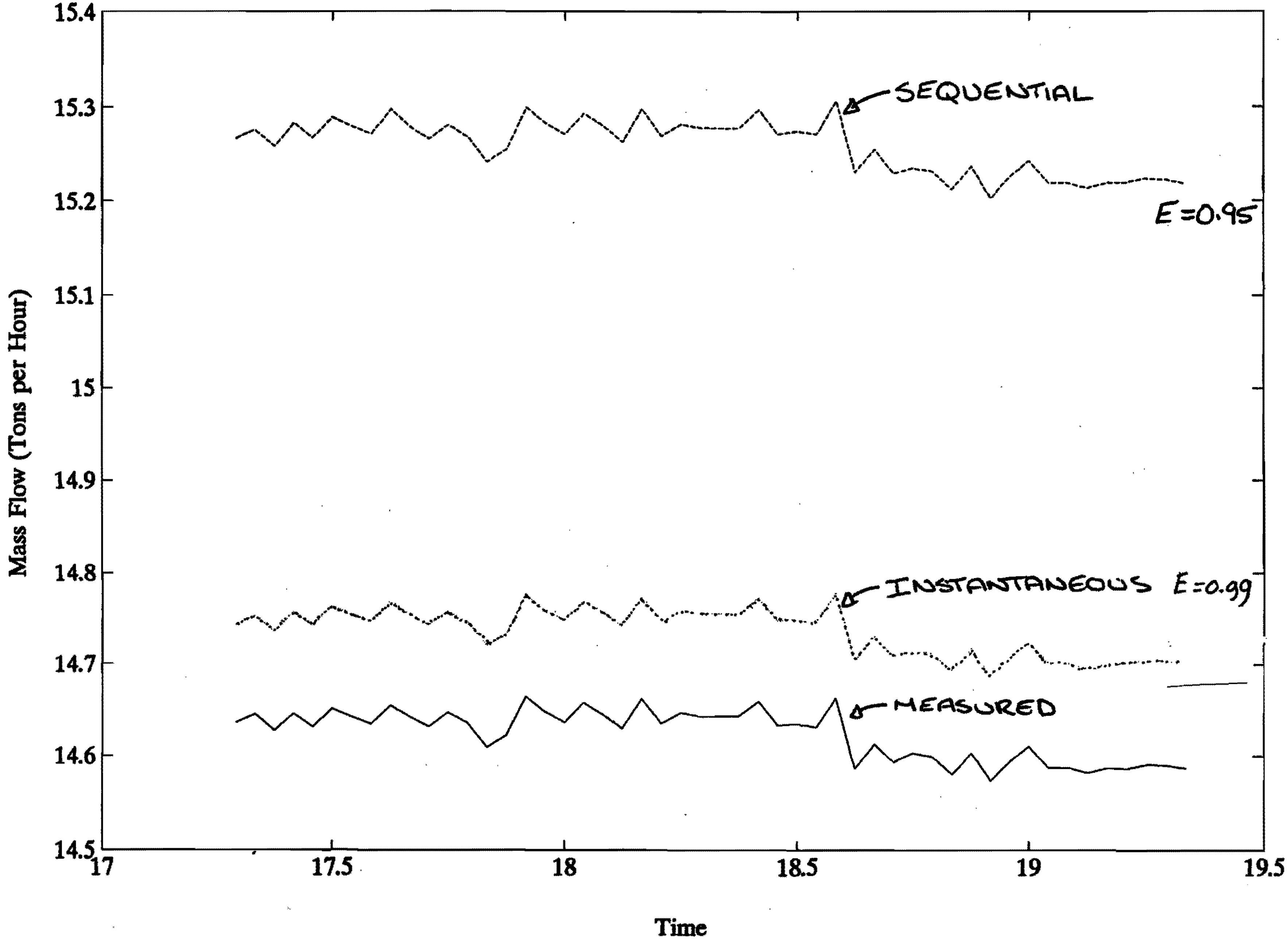
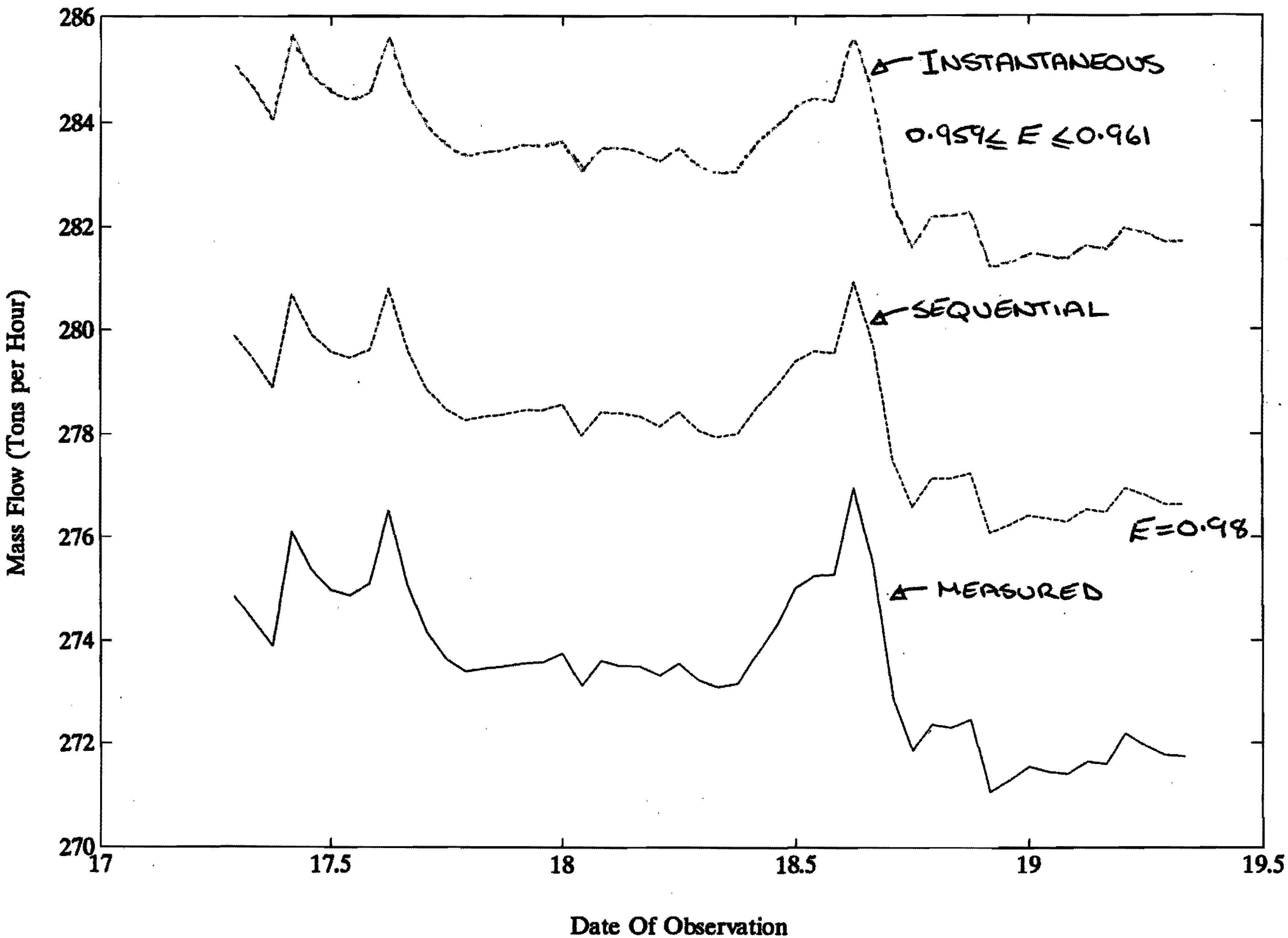

measured value
diagonal
(y2,eta2)
line b
(y1,eta1)
true value
line c

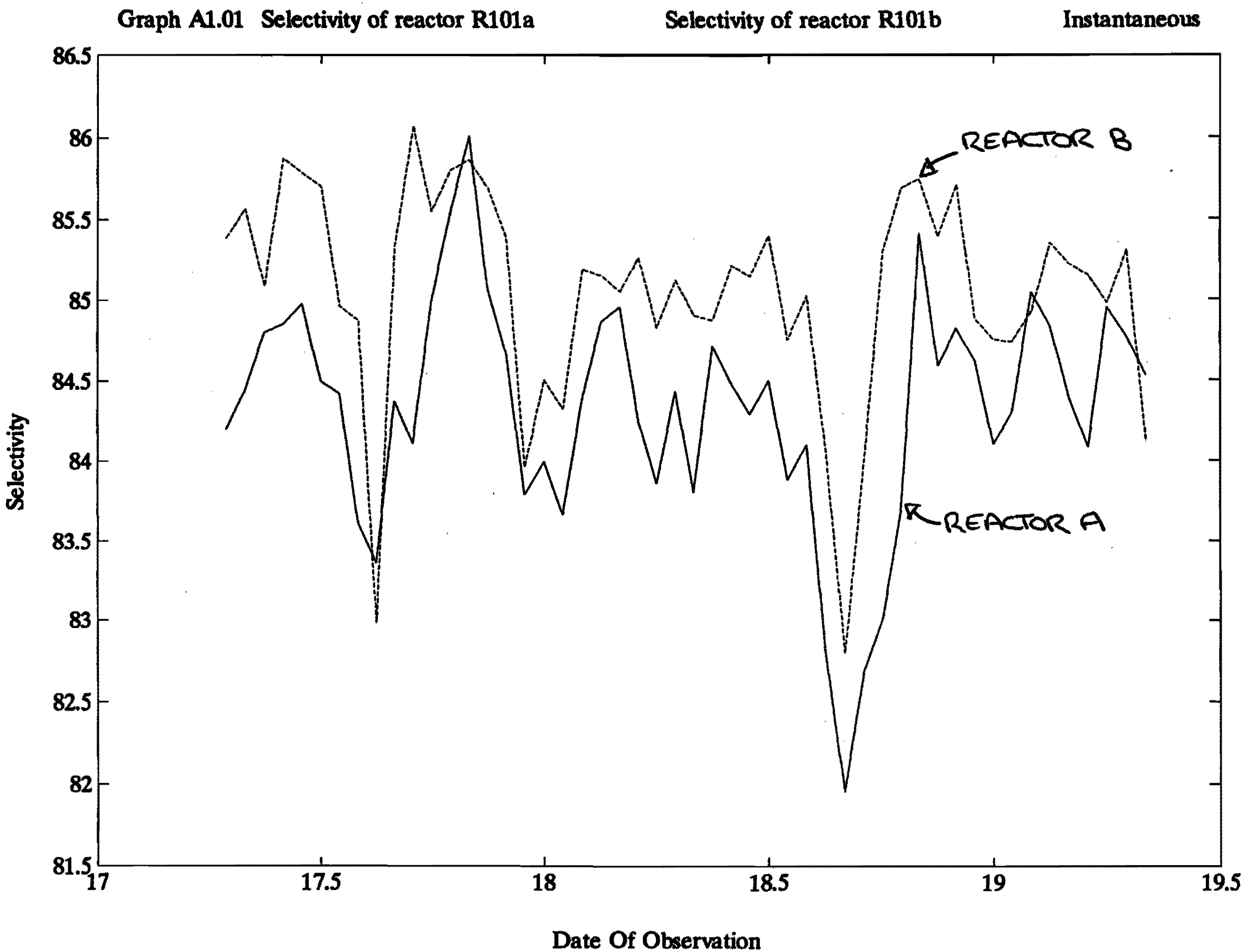
Figuur 1

Graph 1.03   s010 Mass flow of O2 into M101



Graph 1.07 s030 Mass flow into R101a




Graph A1.01 Selectivity of reactor R101a
Selectivity of reactor R101b
Instantaneous
86.5
86
85.5
85
84.5
84
83.5
83
82.5
82
81.5
Selectivity
17
17.5
18
18.5
19
19.5
Date Of Observation
REACTOR B
REACTOR A

Graph B1.01 Selectivity of reactor R101a Selectivity of reactor R101b Sequential

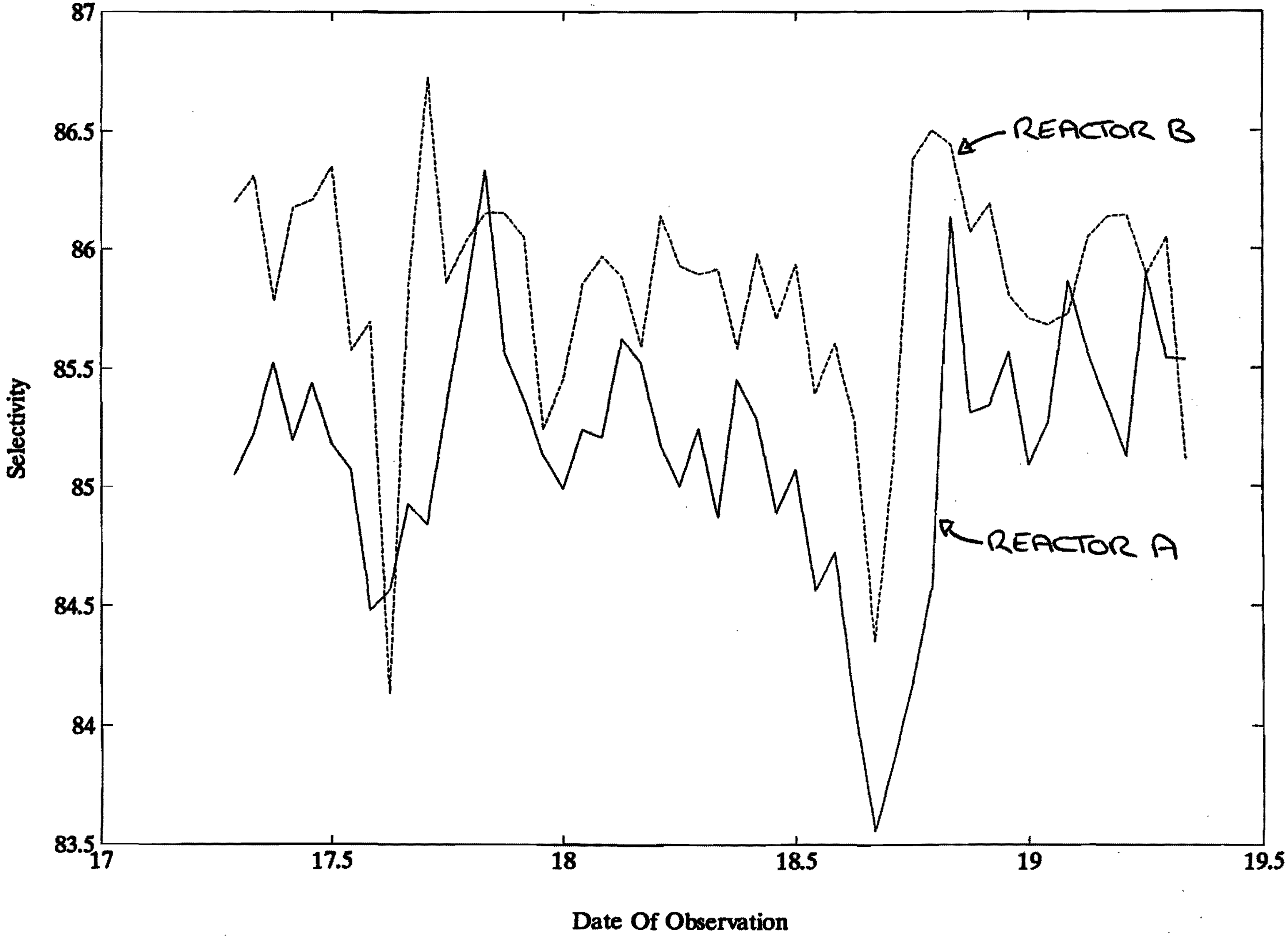


Table a4.2 95% Confidence Intervals For Systematic Error

Variable	Stream (to)	Lower Conf	Mean	Upper Conf	Error
Mass Flow	stream 1 m101	-7.5%	-6.3%	-5.1%	Yes
Oxygen	stream 1 m101	-0.4%	-0.3%	-0.2%	Yes
Mass Flow	stream 2 m101	-0.6%	+0.4%	+1.4%	No
Methane	stream 2 m101	+0.1%	+1.0%	+1.9%	Yes
Ethane	stream 2 m101	+0.2%	+1.0%	+1.8%	Yes
Mass Flow	stream 3 r101a	-2.8%	-0.9%	+1.0%	No
Ethylene	stream 3 r101a	-0.4%	-0.3%	-0.2%	Yes
Oxygen	stream 3 r101a	+0.0%	+0.4%	+0.8%	No
Ethylene Oxide	stream 3 r101a	-2.3%	+0.0%	+2.3%	No
Carbon Dioxide	stream 3 r101a	-0.5%	-0.3%	-0.1%	Yes
Methane	stream 3 r101a	-0.6%	-0.5%	-0.4%	Yes
Ethane	stream 3 r101a	-3.2%	-3.1%	-3.0%	Yes
Argon	stream 3 r101a	-1.3%	-1.1%	-0.9%	Yes
Nitrogen	stream 3 r101a	-0.5%	-0.4%	-0.3%	Yes
Mass Flow	stream 4 r101b	-1.8%	-0.9%	-0.0%	No
Ethylene	stream 5 c203	-0.2%	-0.0%	+0.2%	No
Oxygen	stream 5 c203	-0.6%	-0.4%	-0.2%	Yes
Ethylene Oxide	stream 5 c203	-1.4%	-1.1%	-0.8%	Yes
Carbon Dioxide	stream 5 c203	-0.3%	-0.0%	+0.3%	No
Methane	stream 5 c203	-0.4%	-0.3%	-0.2%	Yes
Ethane	stream 5 c203	-2.2%	-2.0%	-1.8%	Yes
Argon	stream 5 c203	+0.3%	+0.4%	+0.5%	No
Nitrogen	stream 5 c203	+0.1%	+0.1%	+0.1%	Yes
Ethylene	stream 6 c203	-0.2%	-0.0%	+0.2%	No
Oxygen	stream 6 c203	-0.6%	-0.4%	-0.2%	Yes
Ethylene Oxide	stream 6 c203	-1.4%	-1.0%	-0.6%	Yes
Carbon Dioxide	stream 6 c203	-0.3%	-0.0%	+0.3%	No
Methane	stream 6 c203	-0.4%	-0.3%	-0.2%	Yes
Ethane	stream 6 c203	-1.9%	-1.8%	-1.7%	Yes
Argon	stream 6 c203	+0.2%	+0.4%	+0.6%	Yes
Nitrogen	stream 6 c203	+0.1%	+0.1%	+0.1%	Yes
Ethylene Oxide	stream 7 Arbld	-0.3%	+0.0%	+0.3%	No
Water	stream 7 Arbld	-8.4%	-7.7%	-7.0%	Yes
Mass Flow	stream 8 stgas	-2.3%	-0.0%	+2.3%	No
Mass Flow	stream 10 CH4in	-0.9%	-0.4%	+0.1%	No
Ethylene	stream 10 CH4in	-0.0%	-0.0%	-0.0%	No
Mass Flow	stream 12 c201	-1.5%	-0.4%	+0.5%	No
Mass Flow	stream 13 m101	+6.2%	+7.0%	+7.8%	Yes
water	stream 14 xc201	-1.8%	-0.6%	+0.2%	No
Mass Flow	stream 16 xc201	-7.0%	-6.7%	-6.4%	Yes
Water	stream 16 xc201	-1.3%	+0.0%	+1.3%	No
Mass Flow	stream 17 c203	-1.7%	+0.0%	+1.7%	No

Table a4.3 Comparison Of Measurement Devices

Variable	Stream (to)	Lower Conf	Mean	Upper Conf
Mass Flow	stream 3 r101a	-2.8%	-0.9%	+1.0%
	stream 4 r101b	-1.8%	-0.9%	-0.0%
Ethylene	stream 3 r101a	-0.4%	-0.3%	-0.2%
	stream 5 c203	-0.2%	-0.0%	+0.2%
	stream 6 c203	-0.2%	-0.0%	+0.2%
Oxygen	stream 3 r101a	+0.0%	+0.4%	+0.8%
	stream 5 c203	-0.6%	-0.4%	-0.2%
	stream 6 c203	-0.6%	-0.4%	-0.2%
Ethylene Oxide	stream 3 r101a	-2.3%	+0.0%	+2.3%
	stream 5 c203	-1.4%	-1.1%	-0.8%
	stream 6 c203	-1.4%	-1.0%	-0.6%
Carbon Dioxide	stream 3 r101a	-0.5%	-0.3%	-0.1%
	stream 5 c203	-0.3%	-0.0%	+0.3%
	stream 6 c203	-0.3%	-0.0%	+0.3%
Methane	stream 3 r101a	-0.6%	-0.5%	-0.4%
	stream 5 c203	-0.4%	-0.3%	-0.2%
	stream 6 c203	-0.4%	-0.3%	-0.2%
Ethane	stream 3 r101a	-3.2%	-3.1%	-3.0%
	stream 5 c203	-2.2%	-2.0%	-1.8%
	stream 6 c203	-1.9%	-1.8%	-1.7%
Argon	stream 3 r101a	-1.3%	-1.1%	-0.9%
	stream 5 c203	+0.3%	+0.4%	+0.5%
	stream 6 c203	+0.2%	+0.4%	+0.6%
Nitrogen	stream 3 r101a	-0.5%	-0.4%	-0.3%
	stream 5 c203	+0.1%	+0.1%	+0.1%
	stream 6 c203	+0.1%	+0.1%	+0.1%