Analytica Chimica Acta, 190 (1986) 33—44
Elsevier Science Publishers B.V., Amsterdam — Printed in The Netherlands

THE CONTRIBUTION OF QUALITY ASPECTS TO PROCESS CONTROL

JOHN E. RIJNSDORP

Department of Chemical Technology, Twente University of Technology, P.O Box 217, 7500 AE Enschede (The Netherlands)

(Received 25th April 1986)

SUMMARY

Process operators often have difficulties with quality supervision and control for the following reasons: (i) analytical results are infrequent and much delayed, (ii) conventional automatic control cannot sufficiently reduce quality deviations, and (iii) several set values can be candidates for correction of quality deviations. Control performance is discussed with regard to these problems, in relation to the degree of buffering, and types of process perturbations and measuring errors. Some methods are discussed for improving the situation, namely, on-line quality estimation from simpler measurements, and integration of off-line quality measurements and on-line quality measurement and estimation by means of state estimators.

The literature on process control is mostly focussed on the problem of automatic regulation, i.e., keeping easily measured process variables near desired or set values. This achieves several goals: by avoiding abnormal values, safety and equipment availability can be improved, and the influence of external perturbations is reduced, not only on the automatically regulated variables but also on product qualities. A pertinent example is the control of reflux ratio on distillation columns (Fig. 1), which reduces the sensitivity of the top product composition to perturbations, particularly rapid ones [1]. However, usually more precise quality control is required, particularly if strict quality specifications prevail. When "quality give-away" is generally uneconomic, the margin with respect to the specification limit should be made as small as possible. Even in cases which do not have strict quality specifications, it can make sense to avoid large quality variations.

The problem of quality control is aggravated if process control is designed for optimizing rather than regulating the process operation; then variations in process variables are tolerated if this leads to higher efficiency. For instance, some distillation processes require less energy if the pressure is always kept at the minimum value, even if this value fluctuates, instead of being regulated to a constant value [2].

If a suitable on-line quality analyzer is available, fast and precise automatic quality control can be achieved. The choice of control actions will be discussed in the next section. In practice, the main problems with analyzers

0003-2670/86/$03.50

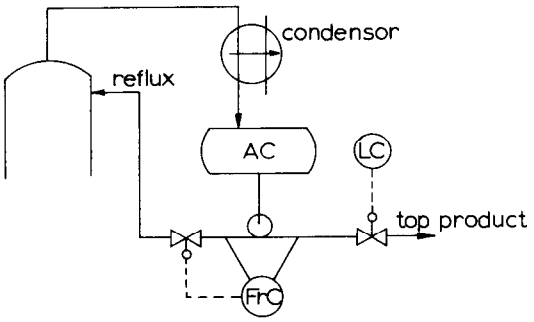


Fig. 1. Reflux ratio control on a continuous distillation column: LC, level control; FrC, flow ratio control; AC, accumulator.

are their relatively low reliability and difficult maintenance, which can lead to relatively poor availability. (Availability can be quantified in the well-known expression: availability = MTTF/(MTTF + MRT), where MTTF is the mean time to failure and MRT is the mean repair time). Consequently, the operators have to take over quality control from time to time.

Modern quality analyzers have built-in microcomputers which, amongst other things, take care of checking and putting the analyzer out of operation in cases of abnormal behaviour. This reduces the probability of malfunctioning, but does not improve availability. If availability is still too low, it is preferable to let the operator take care of quality control, because frequent switching between automatic and manual control is not good for work motivation.

Manual quality control is unavoidable when on-line quality analyzers are not available or simply too expensive. This situation is still relatively manageable if the operator can utilize a local semi-automatic analyzer. But quality control really becomes difficult when samples have to be analyzed in the laboratory. Then the operator has to live with infrequent and sometimes much delayed data. In complex processes, manual quality control is even more difficult because of the interactions between process variables. If there is a deviation in quality, the operator must decide which set points should be adjusted and must asses how this will affect other process conditions. There are two possibilities to assist the operator in manual quality control. The first is to provide an estimate of the relevant product quality, at least during the periods between receipt of direct quality data. The second is to assist the operator in finding the most efficient control action, either directly, or by making him familiar with a system model. These possibilities will be discussed in later sections.

The next two sections are devoted to automatic quality control and, in particular to the effects of product buffering on control algorithms and on the choice of quality measuring instruments.

AUTOMATIC QUALITY CONTROL

The choice of algorithms for automatic quality control depends not only on process dynamics, but also on perturbation dynamics and on the degree of buffering. Figure 2 shows these influences in terms of a block diagram. Here the effects of all outside perturbations (process disturbances, process noise) on the controlled quality are represented by filtered white noise. Of course, the filter characteristics must include the influences of automatic regulation. On the one hand, this tends to reduce low-frequency components in the perturbation effects but, on the other hand, automatic regulation of temperatures, pressures, and flow rates cannot eliminate sustained quality deviations.

If van der Grinten's model for perturbation effects [3] is applicable to this more complicated case, the above-mentioned filter is a first-order one, usually with a rather large time constant. The degree of buffering is small if the pertinent stream flows directly to another process for which the quality is critical. It is large if the pertinent stream flows to a large storage tank, where it is adequately mixed. Of course, when mixing is poor, the material will be layered, hence the effective mixing time constant will be smaller.

In Appendix A, it is shown that the optimal control algorithm contains, to a good approximation, the (first-order) characteristics of the filter representing the input perturbations and of the buffer. When both corresponding time constants are large, the algorithm comes close to "PII²" (proportional plus integral plus double integral action). The small difference is due to the finite gain of the white noise filter, i.e., to the inherent assumption that the outside perturbations have zero average value. Actual perturbations will be asymmetric, which warrants the introduction of integral action.

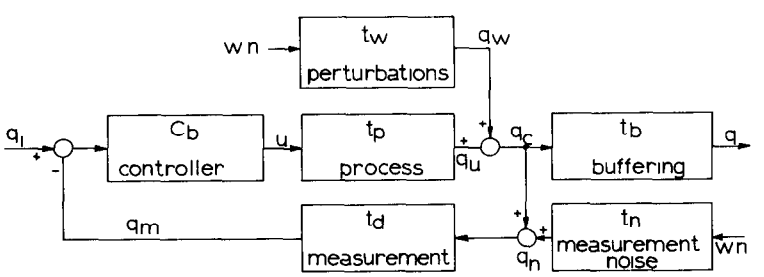


Fig. 2. Block diagram of an automatic quality control system: u, correction; q_u, effect of u on controlled quality; w.n., white noise; q_w, effect of perturbation on controlled quality; q_c, controlled quality; q, quality after buffering; q_i, quality of set value; q_n, effect of measurement noise on measured quality; q_m, measured value of controlled quality; t_w, t_p, t_b, t_n, time constants; t_d, dead time.

Control quality

Evidently, a high degree of product buffering stresses control for the lower frequencies. It also puts more weight on the accuracy of the quality analyzer and less weight on its speed. As a consequence, van der Grinten's rule of thumb for combining speed and accuracy [4, 5], which was derived for zero buffering, is no longer applicable. Appendix A gives the derivation of a more appropriate, though less simple rule. The difference will be illustrated for a simple example; Table 1 gives the input data and results.

The controllability or measurability ratio (c.r.) as defined by van der Grinten [4]:

$$\text{c.r.}^2 = 1 - (\sigma_e/\sigma_p)^2 \tag{1}$$

where σ_e is the standard deviation of the error in the relevant quality (after buffering); and σ_p is the standard deviation of the perturbation effects on the relevant quality (after buffering). It can be seen that without buffering the off-line measurement is inferior to the on-line measurement. With buffering, the opposite is true.

In general, the results depend strongly on the characteristics of the measurement errors. If these can be nicely separated into a constant systematic error, and a rapidly fluctuating random error, then control quality is favourable; the systematic error is compensated once and for all by calibration, and the effects of the random errors are suppressed by process and buffer. However, if the measuring errors contain dynamic phenomena, such as drift, then the controllability deteriorates. This is particularly true when the characteristic time constant in the drift phenomena is of the order of the filtering time constant in the perturbation effects. Evidently, a good dynamic model of measurement errors is necessary for evaluating control quality.

TABLE 1

Control quality without and with buffering[a]
(σ_w = 10%; t_w = 10 h; t_b = 20 h.)

Ease	σ_n (%)	t_n (h)	t_d (h)	Controllability ratio	
				No buffer	With buffer
Off-line	1	1	2	0.815	0.9976
On-line	3	1	0.5	0.877	0.9900

[a] σ_w is the relative standard deviation of the total effect of input perturbations on the controlled quality; t_w is the filtering time constant in this effect; t_b is the buffering time constant; σ_n is the relative standard deviation of the measuring errors; t_n is the correlation time constant of the measuring errors; and t_d is the dead time in the control loop (usually mostly in the measurement).

ESTIMATION OF PRODUCT QUALITIES

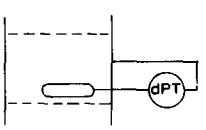
Use of "conventional" measurements

In many cases, off-line quality measurements offer accurate, but delayed and less frequent, information about product qualities. During the intervals, conventional measurements (such as pressures, temperatures, flows and levels) can be used for rapid estimation of product qualities. The lower accuracy is not a drawback here, as the quality data can be utilized for real-time calibration.

The main problem is to develop appropriate algorithms for calculating the quality estimates from the conventional measurements. When little is known about process behaviour, one can try to generate an empirical algorithm. Of course, when adequate process models are available, much time and effort can be saved by following a more deductive approach.

In many chemical plants, the products are separated by one or more distillation columns. As much is known about distillation, it makes sense to develop algorithms in a deductive way for estimating product quality from the volatilities on a number of trays. These volatilities can be measured sensitively by means of differential vapour-pressure cells (Fig. 3). These cells measure the difference between the vapour pressure on a distillation tray and the vapour pressure in a sealed bulb partially filled with the desired product, in good thermal contact with the vapour on the tray. The bulb is filled with the desired component, so that the difference in vapour pressure is an indication of the impurities in the tray mixture.

Appendix B shows preliminary results for a simple case with three components. A weighted difference of two tray volatilities gives a good estimate of top product purity (about 4% error). As the measurements are continuous, and have little delay, the estimate is relatively fast, certainly compared to laboratory analysis.



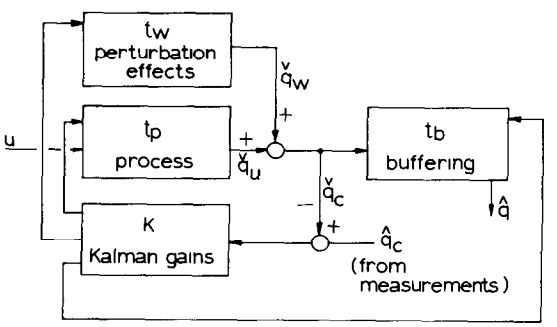


Fig. 3. Differential vapour-pressure cell.

Fig. 4. State estimation.

For other processes, other solutions have to be found. Jo and Bankoff [6] gave an example for a polymerization process, in which the molecular weight is estimated from on-line measurements of viscosity and refractive index. Of course, these measurements are more difficult than those of pressure, temperature, etc., but still relatively easy compared to on-line measurement of molecular weight.

Combining on-line and off-line measurements

The final problem to be discussed is how to assist the operator in combining on-line quality estimates with on-line and off-line quality measurements. A conventional approach is to correct the on-line estimation whenever off-line data become available. However, in this way, time differences and other dynamic effects are not taken into account, which decreases the accuracy, particularly during and after large perturbations in the process.

Dynamic effects can be properly included by utilizing a state estimator, e.g., a Kalman filter [7, 8]. Figure 4 shows a simplified block diagram. The system state is predicted by a system model which, for the case shown in Fig. 1, consists of the filter producing the perturbations, the process time constant, and the buffering time constant. The predicted state is immediately corrected by the on-line quality estimation data, according to the well-known expression:

$$\hat{\mathbf{x}} = \check{\mathbf{x}} + \mathbf{K}(\hat{q} - c^{\mathrm{T}}\check{\mathbf{x}}) \tag{2}$$

where x is the state vector (with the above-mentioned components), q is the on-line quality estimation, K is the Kalman-gain vector, c provides for selecting the relevant quality from the state vector, T indicates the transpose of a vector, $\check{}$ indicates a prediction and $\hat{}$ indicates an estimate.

For incorporation of delayed (off-line) data, e.g., obtained from laboratory analyses, a suitable approach has been presented by Kok and van Wijk [9]: as soon as such data become available, the state estimator is jumped back to the moment when the sample was taken, and the state is corrected by an expression similar to Eqn. 2. Then the state estimator is brought back to the present moment of time on a fast time scale. In this way, the state estimate always includes all available quality information. Of course, this approach requires much memory space for storing historic data, but with modern computers this is no longer a problem.

On the basis of state estimation, optimal (in the linear/quadratic sense) control actions can be calculated [10]. These can be presented to the operator (advisory control). Such an approach is particularly useful when the system has several possible inputs for correction (usually set points of conventional control loops). Then the algorithm can also provide assistance in choosing the best input.

Conclusions

Product buffering puts more weight on quality control for low frequencies resulting in control algorithms with double integral action.

Measurement accuracy tends to become more important compared to speed of response when product buffering is stronger and measuring errors are changing more gradually.

On-line quality estimation, based on simple measurements and computer algorithms, nicely complements off-line quality measurements, particularly if the latter are infrequent and much delayed. On-line quality estimations, and on-line and off-line quality measurements are best combined by a state estimator.

APPENDIX A

OPTIMAL CONTROL ALGORITHM AND CONTROL QUALITY

General approach

Wiener's method [11] requires the conversion of the feed-back control scheme (see Fig. 2) to an equivalent feed-forward control scheme (see Fig. 5). Here, w is the external perturbations effect, as filtered by the buffer; n is the same, for the measurement noise; u is the correction signal to the process; q_u is the effect of this correction on the controlled quality; q_w is the effect of w on the controlled quality; q is the controlled quality; t_w is the perturbation filtering time constant; t_n is the measurement noise filtering time constant; t_b is the buffering time constant; t_p is the major process time constant; t_d is the effective dead time (usually caused mainly by the quality measurement); σ_w is the standard deviation of the perturbations (before buffering), and σ_n is the same for the measurement noise.

The following frequency spectra are found:

$$\Phi_{ww} = 2t_w \sigma_w^2 / [1 + (\omega t_w)^2][1 + (\omega t_b)^2] \tag{A1}$$

$$\Phi_{nn} = 2t_n \sigma_n^2 / [1 + (\omega t_n)^2][1 + (\omega t_b)^2] \tag{A2}$$

$$\Phi_{zz} = \Phi_{ww} + \Phi_{nn} = 2t_w \sigma_w^2 (1 + C^2)[1 + (\omega t_0)^2] / [1 + (\omega t_w)^2][1 + (\omega t_b)^2][1 + (\omega t_n)^2] \tag{A3}$$

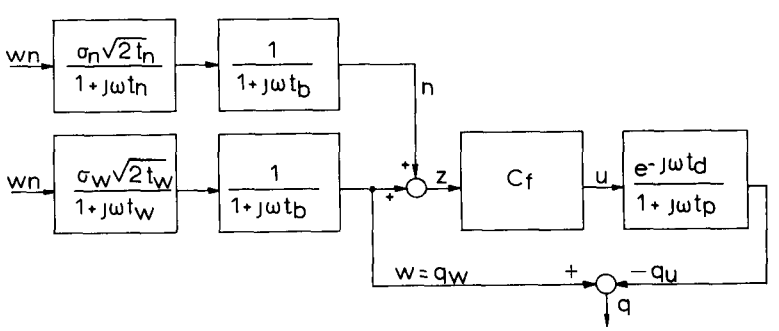


Fig. 5. Block diagram of feed-forward controller.

where $C^2 = t_n \sigma_n^2 / t_w \sigma_w^2$ and $t_0^2 = (t_n^2 + t_w^2 C^2)/(1 + C^2)$.

Wiener's method yields the following expression for the optimum feed-forward controller:

$$C_{f,opt} = [(1 + j\omega t_p)/\Phi_{zz}^+] \, \mathcal{L}F^{-1} [(\Phi_{ww}/\Phi_{zz}^-) \exp(j\omega t_d)] \tag{A4}$$

where Φ_{zz}^+ is the positive factor of Φ_{zz}, Φ_{zz}^- is its negative factor, F^{-1} indicates inverse Fourier transform, and $\mathcal{L}$ indicates Laplace transform.

Substitution into Eqn. A4 yields for the part between brackets:

$$\sigma_w (2t_w)^{1/2} \exp(j\omega t_d)(1 - j\omega t_n)/(1 + j\omega t_w)(1 + j\omega t_b)(1 - j\omega t_0)(1 + C^2)^{1/2}$$

and separation into partial fractions:

$$[A_1 \exp(j\omega t_d)/(1 + j\omega t_w)] + [A_2 \exp(j\omega t_d)/(1 + j\omega t_b)] + [A_3 \exp(j\omega t_d)/(1 - j\omega t_0)]$$

where

$$A_1 = \sigma_w (2t_w)^{1/2} (1 + t_n/t_w)/(1 + C^2)^{1/2} (1 - t_b/t_w)(1 + t_0/t_w)$$

$$A_2 = \sigma_w (2t_w)^{1/2} (1 + t_n/t_b)/(1 + C^2)^{1/2} (1 - t_w/t_b)(1 + t_0/t_b)$$

$$A_3 = \sigma_w (2t_w)^{1/2} (1 - t_n/t_0)/(1 + C^2)^{1/2} (1 + t_w/t_0)(1 + t_b/t_0)$$

Taking the inverse Fourier transform and the Laplace transform gives

$$[A_1 \exp(-t_d/t_w)/(1 + j\omega t_w)] + [A_2 \exp(-t_d/t_b)/(1 + j\omega t_b)]$$

which can be written in the form

$$[\sigma_w (2t_w)^{1/2}/(1 + C^2)^{1/2}][A_0(1 + j\omega t_1)/(1 + j\omega t_w)(1 + j\omega t_b)] \tag{A5}$$

with

$$\begin{aligned} A_0 &= [(1 + C^2)^{1/2}/\sigma_w (2t_w)^{1/2}][A_1 \exp(-t_d/t_w) + A_2 \exp(-t_d/t_b)] \\ A_0 t_1 &= [(1 + C^2)^{1/2}/\sigma_w (2t_w)^{1/2}][A_1 t_b \exp(-t_d/t_w) \\ &\quad + A_2 t_w \exp(-t_d/t_b)] \end{aligned} \tag{A6}$$

Substitution into Eqn. A4 yields for the optimum feed-forward controller:

$$C_{f,opt} = A_0(1 + j\omega t_p)(1 + j\omega t_n)(1 + j\omega t_1)/(1 + C^2)(1 + j\omega t_0) \tag{A7}$$

Optimal feed-back controller

The feed-back controller follows from

$$C_{b,opt} = C_{f,opt}/(1 - C_{f,opt} G)$$

where G is the process response (see last block in Fig. 5). Hence:

$$C_{b,opt} = \frac{[A_0/(1 + C^2)](1 + j\omega t_p)(1 + j\omega t_n)(1 + j\omega t_1)/(1 + j\omega t_0)}{1 - [A_0/(1 + C^2)](1 + j\omega t_n)(1 + j\omega t_1) \exp(-j\omega t_d)/(1 + j\omega t_0)}$$

with a second-order Pade approximant for the dead time:

$$\exp(-j\omega t_d) \approx (1 - j\omega t_d/2)/(1 + j\omega t_d/2)$$

$$C_{b,opt} \approx \frac{A_0(1 + j\omega t_p)(1 + j\omega t_n)(1 + j\omega t_1)(1 + j\omega t_d/2)}{(1 + C^2)(1 + j\omega t_0)(1 + j\omega t_d/2) - A_0(1 + j\omega t_n)(1 + j\omega t_1)(1 - j\omega t_d/2)} \tag{A8}$$

If the measurement noise can be neglected, Eqn. A6 can be simplified: $C = 0$; $t_n = 0$; $t_0 = 0$; $A_1 = t_w\sigma_w(2t_w)^{1/2}/(t_w - t_b)$; $A_2 = -t_b\sigma_w(2t_w)^{1/2}/(t_w - t_b)$. And, as usually $t_d \ll t_w, t_b$:

$$A_0 \approx \{t_w[1 - (t_d/t_w) + \tfrac{1}{2}(t_d/t_w)^2] - t_b[1 - (t_d/t_b) + \tfrac{1}{2}(t_d/t_b)^2]\}/(t_w - t_b)$$
$$\approx 1 - t_d^2/2t_w t_b$$

and

$$A_0 t_1 \approx [t_w t_b/(t_w - t_b)]\left\{[1 - (t_d/t_w) + \tfrac{1}{2}(t_d/t_w)^2] - [1 - (t_d/t_b) + \tfrac{1}{2}(t_d/t_b)^2]\right\}$$
$$\approx t_d - \tfrac{1}{2}t_d^2(t_w + t_b)/t_w t_b$$

Introduction into the denominator of Eqn. A8 yields

$$(t_d^2/2t_w t_b)\left\{1 + j\omega(t_w + t_b) + (j\omega)^2 t_w t_b + \text{terms with } j\omega t_d\right\}$$
$$\approx (t_d^2/2t_w t_b)(1 + j\omega t_w)(1 + j\omega t_b)$$

Hence, the optimal controller can be approximated by

$$C_{b,opt} \approx (2t_w t_b/t_d^2)(1 + j\omega t_p)(1 + j\omega\tfrac{3}{2}t_d)/(1 + j\omega t_w)(1 + j\omega t_b)$$

If t_b and t_w are relatively large, this is close to a proportional plus integral plus double integral algorithm:

$$C_{b,opt} \approx (3t_p/t_d)(1 + 2/j\omega 3t_d)(1 + 1/j\omega t_p)$$
$$\approx (3t_p/t_d)\left\{1 + [(2/3t_d) + (1/t_p)](1/j\omega) + 2/3t_d t_p)[1/(j\omega)^2]\right\}$$

Control quality

The control quality can be expressed in terms of van der Grinten's controllability or measurability ratio (c.r.) [3, 4]:

$$\text{c.r.}^2 = (\sigma_p^2 - \sigma_e^2)/\sigma_p^2 = \sigma_u^2/\sigma_p^2$$

where σ_e is the standard deviation of q, σ_p the standard deviation of q_w and σ_u the standard deviation of q_u. σ_p follows from integrating Eqn. A1 over all frequencies:

$$\sigma_p^2 = (1/2\pi)\int_{-\infty}^{\infty}\left\{2t_w\sigma_w^2\,d\omega/[1 + (\omega t_w)^2][1 + (\omega t_b)^2]\right\} = t_w\sigma_w^2/(t_w + t_b)$$

σ_u^2 can be determined by a similar derivation:

$$\sigma_u^2 = (1/2\pi) \int_{-\infty}^{\infty} \left\{ 2t_w \sigma_w^2 A_0^2 [1 + (\omega t_1)^2] \, d\omega / (1 + C^2)[1 + (\omega t_w)^2][1 + (\omega t_b)^2] \right\}$$

The result is

$$\sigma_u^2 = [A_0^2/(1 + C^2)] \, [(t_w t_b + t_1^2)/t_b(t_w + t_b)] \, \sigma_w^2$$

Hence the controllability ratio is

$$\text{c.r.}^2 = [A_0^2/(1 + C^2)][1 + (t_1^2/t_w t_b)]$$

APPENDIX B

ESTIMATION OF TOP PRODUCT PURITY FROM VOLATILITIES ON DISTILLATION TRAYS

Distillation columns are widely applied for obtaining products in pure form, commonly as a top product. The unavoidable impurities are of two types. First, those more volatile than the desired product (the "light ends") cannot be influenced by the distillation column and have to be controlled by an upstream process. Secondly, those less volatile than the desired product, among which is the so-called "heavy-key" component, can be controlled locally. For a given purity, small fluctuations in the former have to be compensated by corrections in the latter. If large fluctuations in the concentrations of the light-ends cannot be avoided, the distillation column can be provided with a so-called pasteurizing section (Fig. 6). Then the desired product is withdrawn as a side-stream from a certain number of trays below the top.

Starting with a given composition at the top, it is quite straightforward to make tray-to-tray calculations going down the column. These yield volatilities on each (theoretical) tray. By applying multiple regression to the results, expressions can be found for estimating the top product purity from suitably chosen tray volatilities.

By way of example, the case discussed has three components: one light-end, the light key (the desired product), and the heavy key. For simplicity, relative volatilities (with respect to the light key) are taken as constant. Table B1 summarizes the input data. The resulting tray volatilities (expressed in terms of K values for the light-key component) are given in Table B2.

Multiple regression, with the values for trays 1 and 5 below the top

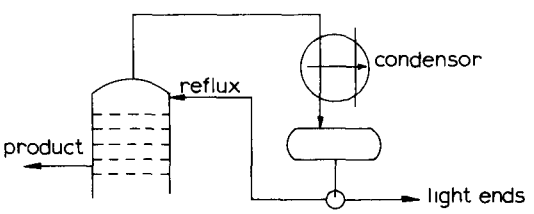


Fig. 6. Pasteurizing section.

TABLE B1

Input data for calculation of volatilities
(Relative volatilities are 2 (light end) and 0.7 (heavy key); reflux ratio 3/1.)

Top compositions (light end, light key, heavy key in each column)								
A	B	C	D	E	F	G	H	I
0.006	0.003	0.009	0.005	0.003	0.007	0.004	0.002	0.006
0.988	0.988	0.988	0.990	0.990	0.990	0.992	0.992	0.992
0.006	0.009	0.003	0.005	0.007	0.003	0.004	0.006	0.002

TABLE B2

K values on trays near the top
(The first column indicates the distance from the top. The next columns give differences of K values for the light-key component with respect to 1, multiplied by 10^5.)

	A	B	C	D	E	F	G	H	I
0	−43	236	−321	−36	150	−221	−29	157	−214
1	152	415	−111	127	302	−49	102	277	−74
2	283	567	−3	236	426	45	189	379	−2
3	392	713	68	327	542	111	262	477	45
4	498	862	128	415	660	169	333	578	85
5	605	1017	185	506	782	225	405	683	128

(the top tray is influenced by subcooling of the reflux, so is better avoided), yields the following result:

$$\text{total top purity} - 1.0008 = 5.31\,(K_{\text{top}-1} - 1) - 3.34\,(K_{\text{top}-5} - 1)$$

The standard deviation of the residual error is about 4% of the standard deviation in the purity variations so, in theory, the expression is a good estimator for the top purity. Of course, various problems have to be solved for practical applications. Amongst others, the variations in K values are very small, hence very sensitive and accurate measurements are required. A proven device is the differential vapour-pressure cell described above (Fig. 3). The coefficients of the regression equation also depend on the reflux ratio, but this can easily be incorporated into the algorithm. Finally, the measurements are done on actual trays, while the analysis is in terms of theoretical trays. Consequently, some form of interpolation is necessary or a tray-to-tray calculation method is to be used with limited tray efficiencies.

REFERENCES

1 O. Rademaker, J. E. Rijnsdorp and A. Maarleveld, Dynamics and Control of Continuous Distillation Units, Elsevier, Amsterdam, 1975.
2 J. E. Rijnsdorp and A. Maarleveld, I. Chem. Eng. Symp. Ser., London Inst. Chem. Eng., 32 (1969) 33.

3 P. M. E. M. van der Grinten and J. M. H. Lenoir, Statistical Process Control (in Dutch), Spectrum, Utrecht, 1973.
4 P. M. E. M. van der Grinten, Statistica Nederlandica, 22 (1968) 43.
5 F. A. Leemans, Anal. Chem., 43 (1971) 36A.
6 J. H. Jo and S. G. Bankoff, AIChE J , 22 (1976) 361.
7 H. Kwakernaak and R. Sivan, Linear Optimal Control Systems, Wiley, New York, 1972.
8 H. Kwakernaak, Regelungstechnik, 16 (1968) 57.
9 J. J. Kok and R. A. van Wijk, Evaluation of models describing human operator control of slowly responding complex systems, Ph.D. Thesis, Delft Univ. Technol., Delft, 1978.
10 G. Stephanopoulus, Chemical Process Control; an Introduction to Theory and Practice, Prentice-Hall, Englewood Cliffs, NJ, 1984.
11 G. C. Newton, L. A. Gould and J. F. Kaiser, Analytical Design of Linear Feedback Controls, Wiley, New York, 1957.