Paper 194h

Indirect on-line optimization through setpoint control

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Indirect on-line optimization through setpoint control

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Abstract: We address the problem of optimizing operation of a process where there are extra degrees of freedom, and where the optimum is not at some constraint. In practice, there are always unknown disturbances and model uncertainties which make this task complicated. The key idea of this paper is to turn the non-linear optimization control problem into a setpoint control problem. If this can be done, the task of optimizing operation can be realized by simple standard control loops, without the need of solving complex nonlinear optimization problems on-line.

The integrated “Petlyuk” or “dividing-wall” distillation column is used as an example process. The Petlyuk arrangement is an interesting alternative to the conventional cascaded binary columns for separation of multi-component mixtures. As much as 30% energy savings have been reported. The industrial use has been very limited, and difficulties in control has been reported as one reason. The optimal operating point depend strongly on disturbances and design parameters. Thus it seems difficult, in practice, to achieve the potential energy savings without a robust optimizing control strategy. We discuss alternative candidate feedback variables for optimization by feedback control and test a particular variable with promising properties

Keywords:

On-line optimization, process control, Petlyuk distillation, controllability analysis, plantwide control

1. INTRODUCTION

In most chemical processes there are additional degrees of freedom which should be used to optimize the operation. In some cases, the optimum is found at some constraints, and such problems are routinely solved and implemented today using model predictive control, often based on linear models.

A more difficult kind of problem is when the optimum is not at the constraints. An example, is optimal split into parallel streams in the preheating to a crude oil distillation column. The reason these problems are more difficult, is that they are more sensitive to the model, and that the optimal solution may be difficult to implement due to uncertainty. For example, in the preheat split problem, it may be difficult to find the correct optimal split because there is no simple measurement of the energy recovery, which we want to maximize. Also, even if we were able to compute the desired split, it is difficult to implement it exactly in practice.

There are several solutions to these problems: Nonlinear model-based optimization with model updating (an extension of MPC), on-line experimenting methods (e.g. EVOP), and feedback methods.

We focus on the feedback method as it is the simplest, and is the preferred choice if it gives acceptable performance. The main idea in the feedback method is to turn the optimization problem into a setpoint problem. The issue is then to find (if possible) a set of variables which, when kept at their setpoints, ensures optimal operation. For example, in the preheat split-problem, a commonly used feedback solution, is to try to keep the temperatures at the points of remixing at the same value. This often gives reasonably optimal operation.

In theory, a variable directly related to the gradient of the criterion function is the ideal feedback variable. In general it is not always possible to find a feedback variable with the required property of turning the optimization problem into a setpoint problem. However, for processes with a large number of states, and a large number of ways to combine measurements, good candidates may exist, the question is how find and select the best ones.

In industry or in daily life we may use this principle without reflecting on it. A simple daily life example is the process of baking an “optimal cake”, which is a very difficult modeling and optimization problem. However, we know that almost optimal operation is obtained when we use feedback control where the oven temperature is kept at a given setpoint, e.g. 200 °C. Why do we apply temperature control at all in this case? At least we know that if the temperature is to high or to low the result is very bad. So a suitable oven temperature is “characterizing” the optimal result.

In a real plant there will always be unknown disturbances affecting the operation. And if we have a model, this model will have some uncertainties. Thus it is not straightforward to tell which direction a manipulative input shall be moved in order to track the real optimal operation point. In figure 1, we try to illustrate this. Assume the real operating point has been moved off the optimum (or the optimum operating point has changed) due to some unknown disturbance. We try to compute a move based on our model, and due to the combination of model uncertainties and unknown disturbances, the result is most probably wrong. Accurate models and good estimation techniques and effective optimization solvers will reduce the average error. But is there any simpler approach? Our idea is to look for a feedback solution first, and if we can find one, the practical problem of realizing optimizing control can be reduced to a standard setpoint problem

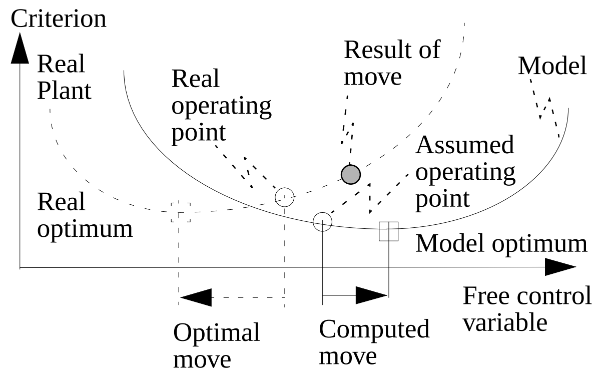

Fig. 1 Optimization problems with unknown disturbances and model uncertainties

We will discuss some basic principles, and we will apply the idea of optimization by feedback is applied to the problem of energy minimization in integrated Petlyuk distillation columns, where there are two degrees of freedom left for energy minimization (the internal liquid and vapor split). We discuss various alternative feedback variables, and propose a viable way of obtaining indirectly on-line energy minimization in such columns.

2. THE IDEAL FEEDBACK VARIABLE

In this chapter we will use a simple approach to describe the properties of an ideal feedback variable. We consider a steady state optimization problem where u is the degrees of freedom, or variables to be used for optimization, and d is an external disturbance which we cannot control. The criterion to be minimized is:

$$\min_{u} \quad J(u, d) \tag{1}$$

For simplicity the assume that the solution is unconstrained, that all directions in u are feasible and that the function J has continuous derivatives up to second order. When the disturbance (d) is changing, we want to adjust the manipulative inputs (u) in a way which always keeps the criterion value at its minimum. The first order necessary conditions is to choose the value of u which gives a zero gradient. Assume we have found the optimal u_0 for a given d_0, then:

$$\left.\frac{\partial J}{\partial u}\right|_{\substack{u = u_0 \\ d = d_0}} = 0 \tag{2}$$

We develop a first order Taylor series expansion for this gradient around the optimum u_0 for the given d_0 (denoted by working point $_0$). Note that the first term will be zero (from 2):

$$\frac{\partial}{\partial u}J(u, d) \approx \left.\frac{\partial J}{\partial u}\right|_0 + \left.\frac{\partial^2 J}{\partial u^2}\right|_0 \Delta u + \left.\frac{\partial^2}{\partial u \partial d}\right|_0 \Delta d \tag{3}$$

The optimal increment in *u* when *d* is changed can be found by keeping the gradient at zero and from (3) we get:

$$\Delta u_{opt} = \left(-\left[\frac{\partial^2 J}{\partial u^2}\right]^{-1} \frac{\partial^2 J}{\partial u \partial d}\right)\Delta d \tag{4}$$

Δu_{opt} express the required change in *u* in order to track the optimum when *d* is changed by Δd. We recognize the Hessian matrix inside the square brackets. Since the solution u_0 gives a minimum of *J*, the Hessian must be positive definite, and then the inverse will exist.

Then we move on, and assume we have a measurement:

$$y = h(u, d) \tag{5}$$

The idea of optimization by feedback is to find some measurement *y* which characterize the optimum in the way that when the measurement (y) is kept constant, by manipulating the degrees of freedom (*u*), the resulting operating point (*u*) will track the optimum, in spite of varying disturbances (*d*). We expand *h* into a first order Taylor series:

$$\Delta y = \frac{\partial h}{\partial u}\Delta u + \frac{\partial h}{\partial d}\Delta d = G\Delta u + G_d \Delta d \tag{6}$$

Ideally, we want a feedback scheme such that making the move $\Delta u = \Delta u_{opt}$ keeps $\Delta y = 0$.

When we put this optimal move into equation (6) and require $\Delta y = 0$, then equation (7) express the ideal properties of *h(u,d)* when *y* is the ideal feedback variable:

$$\frac{\partial h}{\partial u}\left(-\left[\frac{\partial^2 J}{\partial u^2}\right]^{-1} \frac{\partial^2 J}{\partial u \partial d}\right) + \frac{\partial h}{\partial d} = 0 \tag{7}$$

Thus the search is now reduced to find some measurement function *h(u,d)* with these required properties.

An example of this kind of ideal measurement function is in fact the gradient of the criterion function. The reader may verify that if *y* is a linear transformation of the gradient of *J*,

$$y = h(u, d) = c_1 \frac{\partial}{\partial u} J(u, d) + c_0 \qquad (8)$$

then the condition in equation (7) is fulfilled.

Then the conclusion so far is that if we can measure the gradient of the criterion function under influence of the external disturbance *d*, and optimal solution can be found by adjusting *u* in a way which keeps *y* constant, then the adjusted *u* will be the optimal one. This is really not surprising since keeping the gradient at zero, we are in the stationary optimal point by definition. The simplification is that with this kind of measurement information available we may use a standard PID controller for this task.

The standard objection to this is:

> “You cannot expect to measure the gradient of the criterion function in an industrial process!”

And our answers are:

> “Have anybody tried to look for this kind of measurement information which can be useful for simple feedback solutions.”

3. METHODS FOR EVALUATION OF CANDIDATE MEASUREMENTS

Note that we have not considered the criterion function itself so far. Because the minimum criterion value may both increase or decrease as a function of *d*, but there will always be some minimum for a given *d*. When we shall evaluate the goodness of a real measurement, which is not ideal, we also have to consider the impact on the criterion value, and compare it to the optimal solution. We need a way to search for and analyze candidate variables, and to quantify expected loss for the actual set of possible disturbances for a given process.

The ideal variable is really not required, for practical use we only need to keep operations in a region close to the optimum in order to avoid extensive losses. Small losses can usually be accepted. Like in our cake-baking example, where keeping a suitable oven temperature, ensure the quality to be close to optimal. Not exactly optimal, but close enough for our purpose.

We emphasize that this approach will not generally be feasible for all kind of processes. There will still be complex systems out there where detailed modeling, accurate estimation and an effective optimization algorithms are required in order to get the required performance. Having said this, we recommend to look for feedback variables in order to get simpler solutions for processes where this method is applicable.

It may be quite difficult to spot a candidate measurement with the required properties. In our example with “integrated petlyuk distillation” an intuitive method is used, where we use our knowledge of the steady state properties to search for suitable candidates.

The analysis must also involve dynamic properties of the candidate measurements, when used for feedback control. It does not help if we find a good candidate based on steady state analysis if the interaction with other control loops makes feedback control very difficult in practice.

Optimizing control by use of feedback is also a way to simplify and linearize the process model as seen from a higher level controller. While this kind of optimizing control problems cannot be handled by traditional linear MPC because of the inherent process nonlinearities, the process setpoint response can. And this way of “making the process look linear to the MPC” by closing low level loops by ordinary controllers is a usual way of treating nonlinearities in process industry, so a close to linear model can be used in an MPC. This can be regarded as an important reason for the success of MPC with simple linear models, also for nonlinear processes.

In the previous chapter we presented a simple problem, and we were able to determine if a given measurement function has the ideal properties.

On a real process, we cannot expect to find obvious solutions. In order to approach a certain process unit or plant, we can start to quantify the effect of using certain measurements as feedback variables for optimization.

Skogestad and Postlethwaite (1996) present a method for selecting the best candidate feedback variables from a set of available alternatives. This is also treated by *Morud (1996).* It is based on minimizing the worst case loss when $u \neq u_{opt}$

$$\text{Worst-case loss:} \quad \Phi \overset{\Delta}{=} \max_{d \varepsilon D} \left| J(u, d) - J(u_{opt}, d) \right| \tag{9}$$

Here D is the set of possible disturbances. As “disturbances” we should also include changes in operation point and model uncertainty. If we compute u by a feedback controller (C) from the measurement *(y)*, we can express this in terms of the steady state measurement matrices G and G_d. So for a set of G and G_d matrices which represent the worst case loss, we can choose the one which minimize Φ. We can put a requirement on how large worst-case loss we can accept, and if that cannot be fulfilled, none of the available candidates will be acceptable, and other methods of optimizing control must be applied.

4. THE PETLYUK DISTILLATION COLUMN

The thermally integrated “Petlyuk” arrangement implemented in a single distillation column shell has several appealing features. For the separation of a three-component mixture, *Triantafyllou and Smith (1992)* report savings in the order of 30% in both capital and energy costs compared to traditional arrangements with binary columns in series.

An important question remains: Is this process units difficult to operate and is it possible to achieve in practice the energy savings?

The Petlyuk column, shown in Fig. 2, has at steady state, five independent manipulated inputs: Boilup (V), reflux (L), mid product side-stream flow (S), liquid split (R_l) and vapor split (R_v). There may be up to four product specifications: Purities of top (x_{Da}) and bottom (x_{Bc}) products, purity of side-stream product (x_{Sb})and the ratio of the light and heavy impurity components in the side-stream product (x_{Sa}/x_{Sc}).

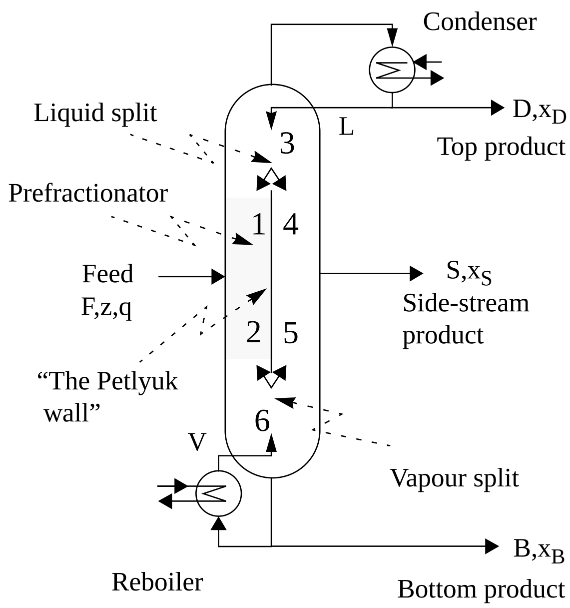

Fig. 2 The Petlyuk Distillation Column

The objective of control is to keep the purity of the main component in all three product stream at specifications. Due to the fact that we have more manipulative inputs than controlled compositions, the remaining two manipulative variables can be used for other purposes, and in particular for minimizing the operating cost.

For the Petlyuk column studied in this paper the optimization objective is to use the two extra manipulated inputs (e.g. R_l and R_v) to minimize the energy consumption (V/F).

The issue is then to find a set of variables which, when kept constant at their setpoints, indirectly ensures optimal operation. One seemingly viable solution would be to simply implement the optimal minimum heat input in an open loop fashion (i. e. set $V = V_{min}$). However, there are at least three serious problems:

- Since operation is infeasible if we have $V < V_{min}$, we would need to set $V > V_{min}$.
- Measurement or estimation of the actual V is generally difficult and inaccurate, which makes it even more difficult to keep V close to V_{min}.
- The optimal value V_{min} changes with operation, and it would require a good model and measurements of the disturbances to recompute it.

Thus, this open-loop policy is clearly not viable. As good candidate variables for feedback control we want variables which avoid the three problems above:

- The optimal candidate feedback value should not be at a limit.
- The variable should not have an extremum inside the normal operating range, and in particular not when $V = V_{min}$
- The accuracy of the measurement of the variable should be good.
- The relation of the variable and the optimum should be insensitive to disturbances.
- Finally, the variable should be easy to control, using the available extra degrees of freedom.

Often we may find variables which have an extremum when the criterion functions is at its minimum. These cannot be used for feedback, but may be used in experimental methods, or simply as indicators to process operators.

5. THE PETLYUK COLUMN MODEL

We use a dynamic tray model with the following simplifying assumptions: Constant pressure, constant relative volatilities, constant molar flows, constant tray efficiency, no heat transfer through the dividing wall. This is a very simple model, but it contains the most important properties of a column. The column data can be found in *Halvorsen and Skogestad (1995)*. The column shown in Fig. 2 is modeled with 6 sections (the numbers inside the column are section numbers). A three-component feed, with components *a, b* and *c* is separated into almost pure *a* (97%) in the top product D, almost pure *b* (97%) in the in the side stream S, and almost pure *c* (97%) in the bottom product B. The overall model can be represented on a general state space form:

$$\begin{aligned} d\frac{x(t)}{dt} &= f(x(t), u(t), d(t)) \\ y(t) &= g(x(t), u(t)) \end{aligned} \tag{10}$$

The states x(t) consist of the component holdups on each tray, that is three states for each tray, which we represent using two compositions and the total holdup. For our column the total number of states is 150 (48 trays plus reboiler and condenser). The input, output and disturbance vectors are defined as:

$$\begin{aligned} u &= [L, V, S, R_l, R_v] \\ y &= [x_{Da}, x_{Bc}, x_{Sb}] \\ d &= [F, z_a, z_b, q] \end{aligned} \tag{11}$$

In addition to the y-vector described here, we will propose later some other measurements to be used for optimization purposes.

6. STEADY-STATE SOLUTION

6.1 Optimization Criterion

With 5 control inputs and 3 setpoints specified we have left 2 degrees-of-freedom for optimization. We here choose the two remaining degrees-of-freedom to be R_l and R_v, but note that other choices may be made.

A comprehensive optimization criterion should include product values and energy cost and be based om maximizing the operational profit. But if we specify product purities, then a very suitable criterion, selected here, is to minimize the energy consumption. In this paper, we use boilup rate (V) as the criterion value, and this will be equivalent to use the energy consumption for most columns.

The steady state constrained optimization problem can be written on the following general form:

$$\min_{u} \quad V(x, u, d) \tag{12}$$

$$\frac{dx}{dt} = f(x, u, d) = 0 \qquad h(x, u) \le 0 \tag{13}$$

The first set of equality constraints represents the steady state model, the second set of equality or inequality constraints will typically contain product specifications (e.g. $x_{Da} > 0.97$) and also allowed range for u (e.g $u_{min} \le u \le u_{max}$).

6.2 Steady State Profiles

We here consider the optimal steady state solution with three specified compositions and with the two remaining degrees-of-freedom (R_l,R_v) chosen such that the vapor boilup V (energy consumption) is minimized.

Fig. 3 shows the resulting composition profile. We observe that the prefractionator separates *a* from *c* almost completely. Thus we can regard sections 3+4 as a binary column for separation of *a* and *b*, and sections 5+6 as a binary column for separation of *b* and *c*. The “tricky” part is that the “feed” to 3+4 and 5+6 depends on the control inputs *u*, and that we have the same vapor flow in sections 5 and 4. We observe that the tray with maximum b-composition is the side-stream tray, which intuitively seems reasonable.

Normally, composition measurements along the column are not available, but temperatures, which are closely related to compositions, may be used to obtain important information. A simple temperature model is used here: We just assume that the temperature on a tray (i) is the mole fraction average of the boiling points T_B for each components (j):

$$T_i = \sum_{j = a, b, c} T_{Bj} x_{i, j} \tag{14}$$

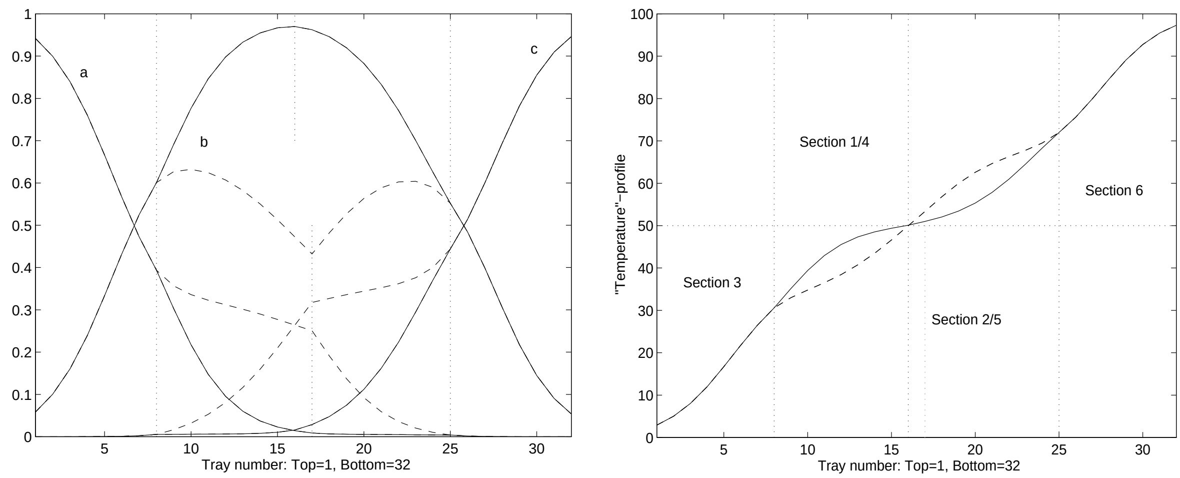

Fig. 3 Compositions (left) of components *a*, *b* and *c* in pre- fractionator (dashed) and main column (solid) and temperatures (right).

6.3 *The solution surface*

We now want to study the sensitivity of the optimal solution to variations in R_l and R_v. The solution of the model equations (13), with R_l and R_v as parameters, can be written as:

$$V = J(R_l, R_v) \tag{15}$$

The solution surface is shown in Fig. 4 and for the “symmetric” case where the feed is 50% vapor (q=0.5). It actually looks like a hull of a ship. The minimum vapor flow is $V_{min} \approx 1.5$, but observe that the vapor flow increase rapidly if we do not keep [R_l,R_v] on their optimal values [0.45 0.49]. In the “worst” direction, which is from the optimum towards P (P is hidden in Fig. 4) or Q, the boilup increase by 50% for a change in R_l or R_v of just 1%. In the “best” direction, which is towards Z or X, R_l *or* R_v can be changed by 0.25 or 50% before the boilup increases by 50%.

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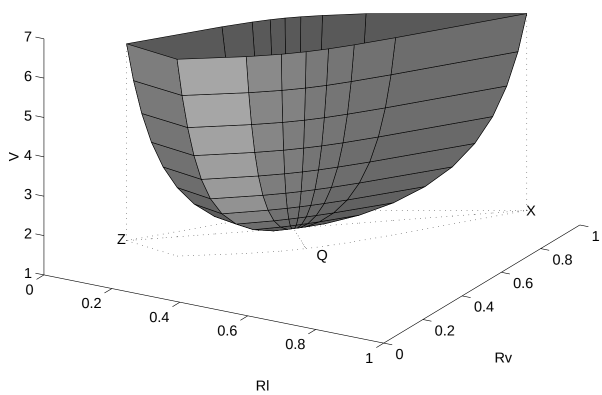

Fig. 4 Optimal solution surface. $V=J(R_l,R_v)$. q=0.5

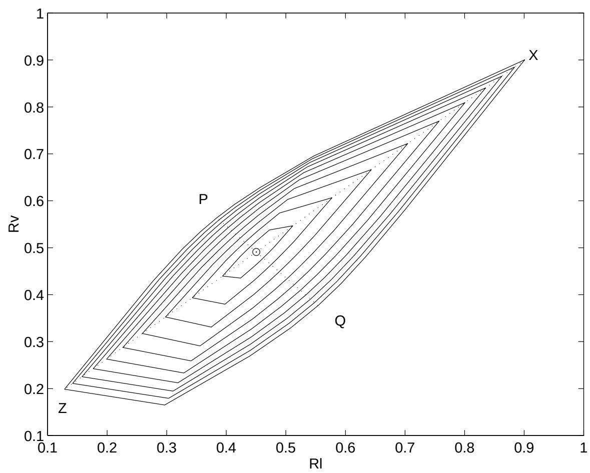

Fig. 4 a. Contour plot of $V=J(R_l,R_v)$. q=0.5 (Note that the change in boilup between contour lines is not constant, but quadratic)

The conclusion of this is that at least one of the remaining degrees-of-freedom (R_l *or* R_v) have to be manipulated by some control algorithm in order to achieve close to optimal operation. But is seems possible that one, for instance R_v can kept constant, but then R_l has to be adjusted to keep the operating point in the bottom of the valley between Z and X

6.4 Effect of disturbances

If disturbances or setpoint changes move the optimum in the PQ direction, then this results in large increases in V unless we adjust R_l *or* R_v in order to remain in the "bottom of the valley". Thus it is of vital interest to know in which direction and how far the optimal operating point in terms of R_l and R_v is moved as a result of a change in a disturbance or setpoint.

In *Halvorsen and Skogestad (1997)* it is shown that changes in the side-stream purity specification and changes in feed liquid fraction will move the surface in the bad PQ direction. Changes in feed composition may also do this, but as feed composition has dimension 2 for a 3-component mixture, we may find a certain "worst" feed change direction which correspond to moving the surface in PQ direction.

7. CANDIDATE FEEDBACK VARIABLES

The results above show that we must at least adjust one of the remaining degrees-of-freedom if close to optimal operation is desired. As mentioned in the introduction, we would like to find some feedback measurement, which when kept constant, would ensure optimal operation.

Candidates for such measurements are composition measurements on individual trays, temperature measurements, and combinations of temperature measurements, and we may also consider flow measurements from individual sections of the column. Temperatures are easy to measure, flows are more difficult, and so are also compositions.

7.1 Prefractionator flow split

Consider the net total material flows from the top of the prefractionator (D'). Note that this is not a single stream like the distillate flow in an ordinary binary column, but a difference between the vapor an liquid flow in the top of the prefractionator. Thus it might become negative if the split ratios are not properly set. As mentioned earlier, sections 3+4 and sections 5+6 can be regarded as two binary columns. The D' or D'/F defines the split in the prefractionator and determines how the mid-component is distributed above and below the dividing wall. Note that D' is also closely related to the net flow downwards in section 4 (denoted $B_4 = L_4 - V_4$). Since D (total distillate flow from the main column) is almost constant, we see that altering D' directly alters B_4. We would expect both D' and B_4 being positive, and also $B_4 < S$

$$D' = V_1 - L_1 \qquad D' = D + B_4 \tag{16}$$

This insight is correct, as we find in non-optimal operating points that B_4 or D' may be negative. This is illustrated for B_4 in Fig. 5, where we see that B_4 (or $D'-D$) changes almost proportionally to the boilup

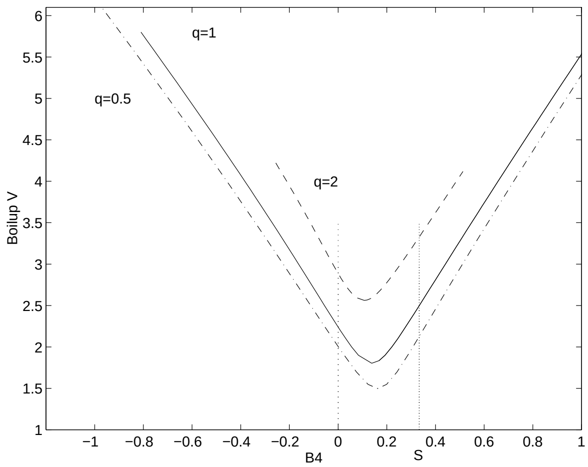

Fig. 5 Boilup as function of net downwards flow above the side stream (B_4 = D'-D) in the "bad" PQ direction of the solution surface (recall Fig. 4).

when we move along the solution surface in the PQ direction. Thus if we were able to measure the net flow *D' or* B_4, then we could achieve close to optimal operation by adjusting R_l to keep *D'* at a setpoint. Unfortunately such a flow measurement is difficult to obtain in practice.

By introducing the split ratios and liquid fraction q of the feed, we can also express D' by external flows L,V and F. From this equation we clearly see how manipulative inputs affects D' and also the close relation to q. We have to compensate changes in q by adjusting split ratios to keep D' close to a certain value.

$$D' = R_v V - R_l L + (1-q)F \qquad (17)$$

7.2 Position of Profile in Main Column.

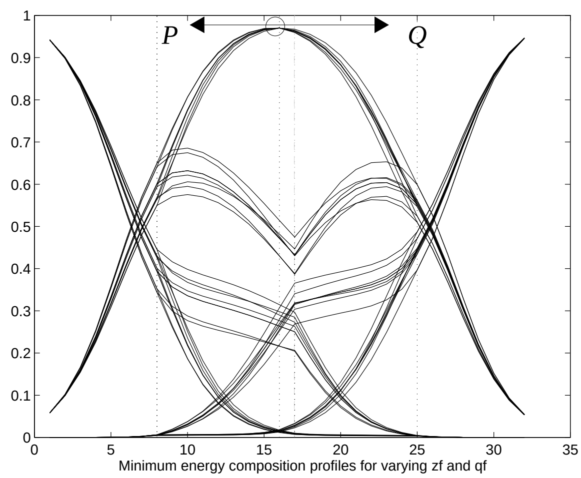

Fig. 6 Optimal composition profiles for varying disturbances. For non-optimal operation towards P or Q directions, the tray number with maximum B-composition will move upwards or downwards

Another important observation is that the maximum composition of the mid-component occurs at the side-stream tray when the column is at its optimum (Fig. 6). This is also approximately true along the bottom of the surface valley. Detecting the actual stage with the maximum value of x_b could thus be a perfect candidate for feedback optimization. However, it is difficult to measure and it also seems to be rather insensitive, so it might be difficult to use in practice

7.3 Temperature Profile Symmetry

Some interesting observations have been made by looking at the symmetry properties of the temperature profile. We define the signed value of the area between the temperature profiles on each side of the dividing wall as a symmetry measurement (DT_S). In a practical application DT_S can be based on or more pairs of difference temperatures in sections above and below feed and side stream.

$$DT_S = \sum(T_{1,i} - T_{4,i}) + \sum(T_{2,i} - T_{5,i}) \qquad (18)$$

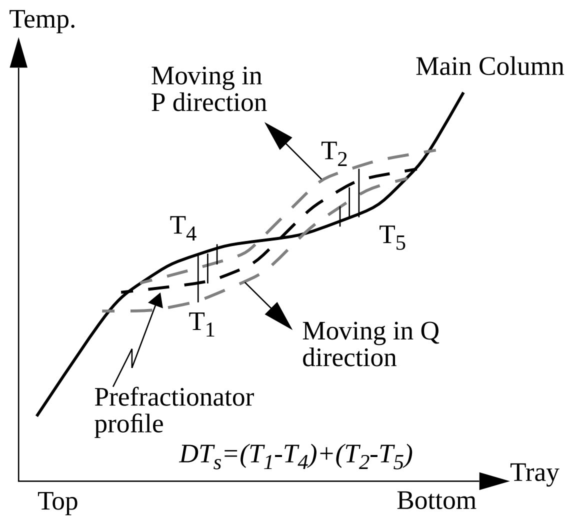

Fig. 7 Illustration of how the temperature profile is changed when moving in the worst direction (PQ) The DT_s symmetry measure will contain "gradient-like" information.

In optimum, the temperature profile is quite symmetric. Interestingly we find DT_S close to zero (symmetric profiles) not only around the optimum, but also along the whole "bottom of the valley" of the solution surface. When we move away from the bottom of the valley in PQ-direction (see Fig. 7) the profile symmetry changes, and the symmetry measure DT_S increases towards P and it decreases towards Q. In Fig. 8 it is shown that if we keep DT_S=k, where k is a constant, this corresponds to an operating line parallel to the bottom of the valley.Unfortunately, the optimal value of DT_s is also sensitive to disturbances, but it may still give important information. DT_s is easy to measure. A practical operating strategy may be to fix R_v, and control the remaining 4x4 system with $[L,V,S,R_l]$ as inputs and $[x_{Da},x_{Bc},x_{Sb},DT_S]$ as measurements. By selecting a suitable setpoint for DT_S we will keep the operating point at a line parallel to the bottom of the optimal surface valley. We may possibly correct the value of DT_S by observing the location of maximum x_b in the main column (see 7.2)

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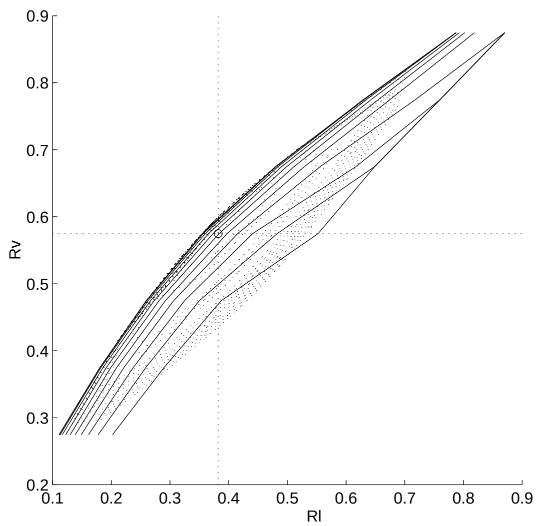

Fig. 8 Operating lines R_l=f(R_v) when DT_s=k for some values of k. Contour lines for constant V is shown

7.4 Temperature difference over prefractionator

Some other variables which have an extremal value when $V = V_{min}$ can also be found. These values can not be used as feedback for setpoint control close to optimum, but may be used as a direct indicator of the criterion value, and for example, in an on-line experimenting method.

One such value is *the temperature difference over the pre-fractionator.* We observe that the temperature difference over the pre-fractionator always has its maximum when the boilup is at its minimum. This temperature difference is related to properties of the composition profile through the simple temperature model in equation (14), so it really reflects optimal separation over the column sections on each side of the dividing wall.

7.5 Evaluation Of Feedback Candidates

A qualitative evaluation is shown in Fig. 9. The criterion function is the cross section of the solution surface in the worst direction (PQ). The most ideal feedback variable found is the position of the mid-component profile in the main column. This variable is not affected by the disturbances at all. But may be difficult to measure or estimate. The other variables are affected by disturbances and setpoints, and this is illustrated by a certain variation around a nominal curve. Thus keeping one of these constant may lead to some variation of the operation on the optimum surface. But still it can a vital improvement compared to keep the additional degrees of freedom at constant values, and use of this simple technology may increase the flexibility in operation and robustness against disturbances considerably.

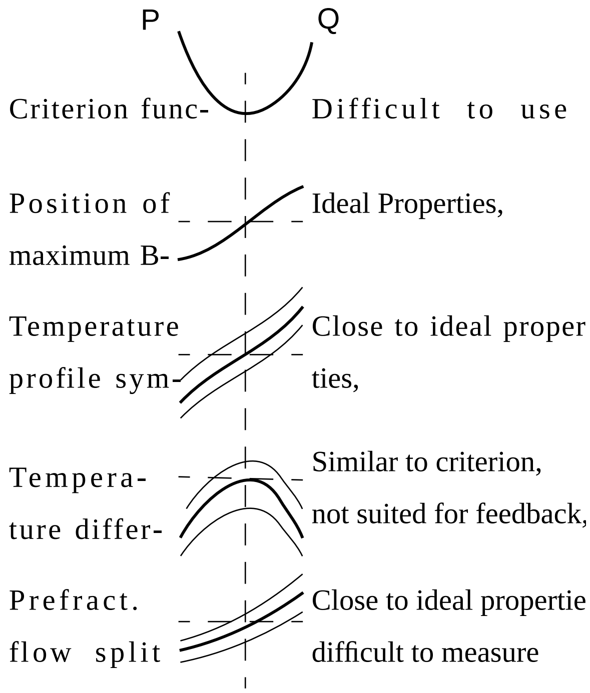

Fig. 9 Quality of some candidate feedback variables

8. SIMULATIONS

The temperature profile symmetry measure (DT_s) is a particular interesting candidate due to that it is an easy and cheap measurement. In this section, some simulation results are presented where DT_s is used as a feedback variable.

Some simple simulation have been done on a column designed for 98%, 96% and 95% product purities in top, middle and bottom respectively. Then we look at the situation when we change setpoints to 99% for all products. Table 1 list the data for the optimal solutions for these two setpoints

	V_{opt}	R_{l_opt}	R_{v_opt}	DT_{s_opt}
I	2.92	0.574	0.637	-9.9
II	6.35	0.643	0.655	-15.0

Table 1: Optimal operating points,
I: 98,96,95% product purities, II: 3x99%purities

If we try to keep $[R_l,R_v]$ constant at the values from I when we change setpoints according to II, the operation is simply infeasible, even with infinite boilup. This is due to that the solution surface is moved, and due to the very steep shape in the worst direction, the split-ratios from I fall outside “the hull” of the surface for II (Refer to case IIa in table 2). If we instead, adjust R_l by a PI controller in order to keep DT_s constant, the result is feasible, and the resulting operating point is 19% above the minimum boilup (Refer to case IIb). Fig. 10 show the dynamic responses from this simulation. If we use the optimal DT_s from I,

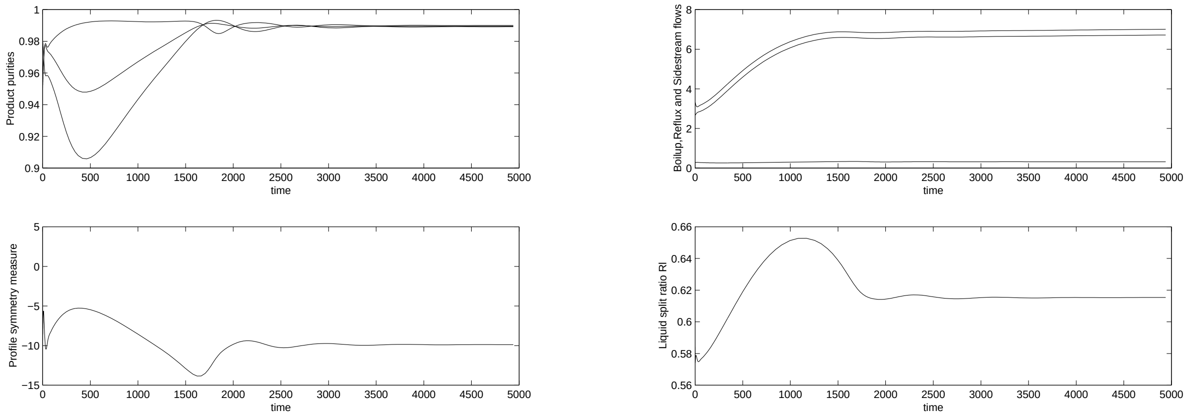

Fig. 10Setpoint step response when increasing purity from 98,96 and 95% to 3x99%, and keeping the DT_s= -9.9 by manipulating R_l. (Ref. IIb)

but still not the optimal vapor split R_v, we get very close to the optimal operating point (case IIc).

The resulting operating points for various approaches are listed below and the results are given in table 2. First we move from setpoints if I to setpoints of II in three different ways:

IIa: R_l and R_v from I, setpoint to II: INFEASABLE

IIb: DT_s and R_v from I, setpoints to II

IIc: DT_s from II, R_v from 1, setpoints to II

Then we do the opposite, start from II and go to setpoints for I.

Ia: R_l and R_v from II, setpoints to I

Ib: DT_s and R_v from II, setpoints to I

Ic: DT_s from I and R_v from II, setpoints to I

	V	*Loss*	R_l	R_v	DT_s
IIa	Infea-sible.	-----	0.574	0.637	----
IIb	7.55	19.0%	0.617	0.637	-9.9
IIc	6.37	0.2%	0.624	0.637	-15.0
Ia	3.65	25.0%	0.643	0.655	-22.5
Ib	2.99	2.5%	0.605	0.655	-15.0
Ic	2.92	0.3%	0.593	0.655	-9.9

Table 2: Operating points for various combinations of setpoints and strategies for adjusting split ratios. The shaded values are kept constant in each case

The results from table 2 are very interesting. It clearly indicates that keeping DT_s at a setpoint keeps the operating point close to the actual optimum, even if we move the whole solution surface by changing the setpoints.

We still observe that the optimal DT_s setpoint is different in I and II, but for this quite large setpoint change in this example, the resulting loss is not very sensitive to the actual DT_s setpoint. And if wee chose a DT_s setpoint close to the optimal one, we get very good results even if we keep the vapor split R_v constant.

Note also that no serious attempt have been done to do optimized tuning of the PI control-loops. Thus the fact that reasonable control performance can be obtained by four coarsely tuned PI controllers, is also an indication on that controlling DT_s by manipulating the liquid split is a feasible approach in practice.

9. CONCLUSIONS

Optimization by feedback control of a suitable measurement variable which characterize the optimum is a very simple approach to optimizing control in cases where unknown varying disturbances and model uncertainties makes optimization difficult to realize in practice.

We have shown some useful relations for ideal feedback variables, and propose an approach for evaluation of candidate feedback variables for a practical systems.

Our process example, the Petlyuk distillation column, will most likely require some kind of on-line optimizing control in order to realize its full potential for reduced energy consumption. This is because the solution surface of the criterion function is quite narrow, and the optimal operation point is very sensitive to certain disturbances.

In this paper we have obtained some relationships between optimal operation and some measurements which can be deduced from the composition profile or the states. These have been evaluated qualitatively for their goodness as feedback variables for setpoint control.

One of these candidates, the temperature profile symmetry measure have been used with success. Temperature measurements are easy and cheap to implement. By keeping this symmetry measure constant we ensure that operation is kept close to the optimum even with changing process conditions. The result is much better than just keeping the split ratios constant. Optimization by feedback should be compared to nonlinear model-based optimization methods, and evaluated for complexity and performance.

10. ACKNOWLEDGEMENTS

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