Implementation issues for real-time optimization of a crude unit heat exchanger network

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This paper provides a case study on the selection of controlled variables for the implementation of real time optimization results in a crude unit heat exchanger network. Two different control strategies with 22 different control structures are evaluated. The idea is to select the controlled variables that give the best plant economic (smallest loss) when there are disturbances (self-optimizing control). The disturbances are correlated and a simple principal component analysis is used to generate a more realistic set of disturbance variations for evaluation of the different control structures. This analysis shows a large variation of loss for different control structures and that a control structure evaluation is necessary to collect the benefits from a RTO system.

1. Introduction

A real time optimization system (RTO) can be described as a sequence of three separate functions, White (1997). (1) Data reconciliation and parameter estimation to establish the current operation point. (2) Optimization to find the optimal operation. (3) Implementation of the optimal result as controller setpoints. Estimated parameters and reconciled process variables are the basis for operations optimization. The optimal operation is computed by maximization of some objective subject to the process model and operating constraints. The objective can be a direct measure of the profit or some function of the variables that when maximized drives the process towards the optimal operation. Finally the computed optimal operation is implemented in the process as setpoints in the control system. The selection of these controlled variables is the main focus of this paper. In the RTO "loop" there is a loss related to uncertainty in the process measurements, estimated parameters, model errors, Forbes and Marlin (1996); Zhang and Forbes (2000).

Optimal values for operation are computed at regular intervals and implemented as setpoints in the control system. In the period from one optimization run to the next the disturbances will change and the current operation is no longer optimal. In addition uncertainties in the controlled variable measurements causes a operation that deviates from the true optimal operation. This disturbance variation and control error is the source of the disturbance and control loss, Skogestad et al. (1998). These losses depends

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highly on the control variables selected for implementation of the optimization result. The objective is to select the control variables such that this loss is minimized.

If some process constraint is active for all expected variations in the disturbances, this variable should be selected as a controlled variable. This is active constraint control, Maarleveld and Rijnsdorp (1970). The variable is then held at its optimal value for all disturbance variations.

If the controlled system has infeasible solutions (constraint violations), with the selected control structure, for normal disturbance variation a back-off from constraints must be computed. The back-off is computed such that the controlled system has feasible solutions for all expected disturbances, Hennin et al. (1994)

To simplify the analysis, several assumptions have been made. The controlled variables selection is solely based on steady state considerations and no evaluation of possible dynamic control problems are made. There are no process model error and estimated parameters and process variables (reconciled values) have no uncertainty. By this assumption the computed optimal values, based on reconciled measurements and model parameters, describes the true process optimum.

2. The optimization problem

A typical process optimization problem has a linear economic objective function, nonlinear process model and some operational constraints. The optimization problem can be formulated as

$$\begin{aligned} \max_x J &= p^T x \\ \text{st.} \quad g(x, d_0, \beta) &= 0 \\ x_{\min} \leq \; x \; &\leq x_{\max} \end{aligned} \tag{1}$$

where the process variables are included in x. The objective, J, is typically product price times product flow minus feed price times feed flow and energy price times energy flow. The process model is included as a equality constraint, $g(x, d_0, \beta) = 0$, where d_0 are the nominal disturbance values β are the model parameters. Inequality constraints are typically bounds on single process variables e.g. high temperature limits or a low flow limit. In this problem there are n variables (in x), m process equations ($g(x, \beta)$) and m_d disturbances. The solution, $x^*(d_0)$, to 1 is referred to as the nominal optimum. The solution to the optimization problem in 1, x^*, is implemented as setpoints to n_f variables using a controller C, where n_f is the available number of degrees of freedom. The controller may be included in the system as a set of linear constraints $Cx = r_0$ where each row in C has one nonzero element, equal to one, corresponding to the selected controlled variable. The controller setpoints equals the nominal optimum, $r_0 = Cx^*$. The controlled system has the solution $x_c(d, r_0)$ and objective $J_c(d, r_0) = p^T x_c(d, r_0)$. A requirement on the controller is that the controlled variables are independent such that the the controlled system has rank equal to the number of variables, i.e. (rank$\left[\frac{\partial g(x, d_0, \beta)}{\partial x}^T |_{x^*, d_0, \beta} \;\; C^T \right]^T = n$)

3. The loss function

The disturbance loss function, Skogestad et al. (1998), is defined as the difference of the optimal objective of some disturbance d, $J^*(d)$ and the objective achieved by using a control structure C, with nominal optimal values as setpoints. The loss function can be written as

$$L_d(d) = J^*(d) - J_c(d, r_0) \tag{2}$$

where $J^*(d)$ is the objective of the optimal operation with a known disturbance d and $J_c(d, r_0)$ the objective of the controlled system using the nominal optimum as setpoints. The disturbance loss function describes the loss of not re-optimizing, and implement new setpoints when the disturbance d has changed and is different from d_0. In addition to the loss of a disturbance change there is a loss due to implementation error or control error. The controlled variables varies around the optimal setpoint due to disturbances, measurement inaccuracy and noise. The control error loss function is defined as

$$L_c(\triangle r_e) = J^*(d_0) - J_c(d_0, r_0 + \triangle r_e) \tag{3}$$

where $\triangle r_e$ is the control error. This definition of loss gives one loss function for each disturbance. A overall scalar measure, for all disturbances and control errors, can be calculated as the sum of the integrals of the disturbance and control error losses from $d_{\min}...d_{\max}$ and $\triangle r_{e\min}...\triangle r_{e\max}$ respectively. With this simplification the loss is calculated along each of the disturbance and control error axis. Other measures, such as the sum of all corner points or the resulting loss of a Monte Carlo simulation could also be used.

4. Disturbance analysis

In the above analysis the aim is to find a controller which minimizes the loss in presence of disturbances. A key issue is to find a good representation of the disturbance variation. The normal range of the disturbance variation should preferably be computed from process measurements. If measured data is unavailable disturbance variations may be estimated based on experience from similar processes and design information.

When a RTO updates the optimal setpoints at regular intervals, a average of the disturbance variation for each interval gives a measure of the expected disturbance change from one optimization run to the next.

In a real process we often have that the disturbances are correlated. Evaluating the loss of one disturbance at a time will fail to evaluate the loss with the most likely combinations of disturbances. By assuming a linear relation and using simple principal component analysis (PCA), Jackson (1991), the measured disturbances may be transformed into a reduced set of uncorrelated disturbances or principal components. The variation range of the principal components is computed as the average variation within each RTO execution interval. The number of principal components used is selected such that the principal components describes the majority (i.e. 90% or 95%) of the variance in the measured data. This representation of the disturbance data provides a more realistic basis for selection of the minimum loss control structure.

5. Case study

In the crude unit the crude (DCR) is preheated in a heat exchanger network where heat is recovered from the hot products and circulating refluxes. As shown in figure 1 the

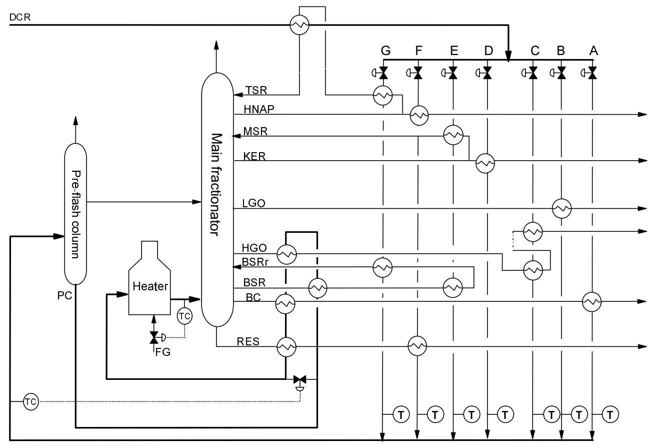

Figure 1. Simplified crude unit overview

cold feed is separated into seven parallel streams (A-G). This feed split provides only 5 degrees of freedom, which is used for optimization, since total feed flow and total bottom circulating reflux (BSR) duty is kept constant. Changes in product yields and BSR duty are the main disturbances to the heat exchanger network. The optimization objective is to save energy by recovering as much heat as possible. The heater is the main energy input in the process and heater outlet temperature is held constant. The minimum energy is then achieved by maximizing the heater inlet temperature. A detailed description of the process, steady state model, data reconciliation and optimization is presented in Lid et al. (2001). For simplicity the operating constraints are ignored in the control structure selection.

5.1. Disturbances

There are 23 disturbance variables. These are the flows and temperatures of streams flowing into the heat exchanger network. The data used in this analysis are 35 days of 12 minutes averages sampled from normal process operation . The RTO execution interval is one hour. The disturbance measurements where reduced to for principal components using PCA as described in section 4. The standard deviation of the selected principal components averaged for all optimization intervals was computed and used as the disturbance variation range.

5.2. Control structure evaluation

There are a large number of possible controllers for implementation of the optimization result. The only controller requirement is that all 5 degrees of freedom in the process must be specified or that the controlled system rank requirement is satisfied. In this case study two control strategies are evaluated.

Strategy 1: the optimal result is implemented as setpoints to the flow controllers in each pass (open loop implementation).

Strategy 2: the optimal result is implemented as setpoints to pass outlet temperature controllers (closed loop implementation) where the temperature controllers manipulates the corresponding pass flow.

The rank requirement for the controller with the open or closed loop implementation strategy may be stated by two simple rules. First, the flow or temperature in pass D and G can not be specified simultaneously since one has to be used to control the total BSR duty. Second, only five of the remaining six flows or temperatures in the seven passes can be specified simultaneously since the total feed flow is to be kept constant. This makes effectively one flow as a dependent variable.

In the open loop implementation strategy there exists 11 different control structures which satisfies the rank requirement. In Table 1 all possible flow control combinations are numbered 1-11 and in Table 2 all possible temperature control combinations are numbered 12-22. For each control structure the disturbance loss, control loss and total loss are computed. The control variable selections in table 1 and 2, are sorted by total loss. The results shows that the best open loop implementation strategy is to select the flow controllers of pass A,B,C,D and E as controlled variables. The setpoints of these controllers is set equal to the current nominal optimum. Pass G is used for total BSR duty control and pass F is used for total flow control. In table 2 the loss functions for different temperature control combinations are listed. The total loss for the best controller is reduced by 57% when the outlet temperature of pass A,B,C,D and E is used as as controlled variables. The selection of pass A,B,C,D and E as controlled variables

Table 1
Strategy 1: Flow control

No.	CV	L_d	$L_{\triangle r_e}$	L
1	ABCDE	0.013	0.009	0.021
4	ACDEF	0.015	0.018	0.034
7	ABCEG	0.040	0.010	0.050
2	ABCDF	0.021	0.031	0.052
6	ABCEF	0.021	0.032	0.053
3	ABDEF	0.023	0.031	0.054
10	ACEFG	0.053	0.020	0.073
5	BCDEF	0.038	0.047	0.084
8	ABCFG	0.068	0.034	0.102
9	ABEFG	0.080	0.034	0.114
11	BCEFG	0.123	0.050	0.173

Table 2
Strategy 2: Temperature control

No.	CV	L_d	$L_{\triangle r_e}$	L
12	ABCDE	0.002	0.007	0.009
15	ACDEF	0.002	0.015	0.017
13	ABCDF	0.005	0.024	0.029
14	ABDEF	0.004	0.025	0.029
17	ABCEF	0.007	0.023	0.030
16	BCDEF	0.006	0.038	0.043
18	ABCEG	0.101	0.054	0.156
21	ACEFG	0.123	0.072	0.195
19	ABCFG	0.183	0.101	0.284
20	ABEFG	0.183	0.105	0.288
22	BCEFG	0.245	0.145	0.390

gives the minimum loss both for the open and closed loop implementation strategy. From table 1 and 2 it is clear that controllers including flow or temperature in pass G and F as controlled variables gives generally a large loss. The difference in loss for the flow control structures may be explained by the fraction of crude flow trough each pass. At the nominal optimum the fractions in pass A-G is [6 15 12 16 10 33 8]% respectively. Pass F has the largest flow and should be used to control the total flow since this will give the smallest relative error in presence of feed flow disturbances. A similar argument applies to the selection of pass E or G to control BSR total duty. The heat transferred from BSR is 4.2MW to pass G and 2.2MW to pass E. The pass receiving the largest duty should be selected to control the total duty in the BSR since this will give the smallest relative change in presence of disturbances. The loss computed using principal components is in general smaller than the loss computed using the disturbances independently. This is explained with the fact that the mass and energy balance in the process is always "zero". If the cold feed flow increases the hot product flows will also increase, if the product yields changes and we have a reduction a hot product flow the product temperature will in general increase. These dependencies in the disturbances seems to cancel some of effect on the total loss.

6. Conclusion

A method for selection of controlled variables for implementation of real-time optimization results based on *self-optimizing control* and the loss function, Skogestad et al. (1998),is described. The analysis is solely based on steady state considerations and no evaluation of the resulting control problem is made. The selection is based on how the controlled process will act in presence of disturbances compared to optimal operation. Some control structures are proposed and evaluated in presence of disturbances and control errors. The minimum loss control structure is achieved by selecting the outlet temperature of pass A,B,C,D and E as controlled variables. The worst case loss, using temperature control, is 0.39°C which is more than 10% of the total RTO potential. This shows that a proper selection of controlled variables is vital for achievement of maximum RTO benefits in presence of disturbances.

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