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A Self-Optimizing Strategy for Optimal Operation of a Preheating Train for a Crude Oil Unit

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Abstract

We apply a recently developed approach for optimizing heat exchanger networks with stream splits to the case study of a preheating train of the crude oil unit at the Mongstad Refinery in Norway. To maximize heat transfer, we adjust the split such that the "Jäschke Temperatures" assume equal values for each branch. For a branch with one heat exchanger, the Jäschke Temperature is calculated as $T_J = \frac{(T-T_0)^2}{T_h-T_0}$, where T is the temperature of the split stream at the heat exchanger exit, and T_h and T_0 are inlet temperatures of the hot and cold stream, respectively. Controlling the Jäschke Temperatures to equal values gives near-optimal operation despite varying flow rates, stream temperatures, and heat transfer coefficients. We fitted a model to plant data obtained from the refinery, and consider two cases with decentralized PI control, and one case where the Jäschke Temperatures are controlled by a model predictive controller. Our paper demonstrates that controlling the Jäschke Temperatures of each branch to equal values is a simple alternative to online real-time optimization methods. Moreover, it is significantly cheaper to implement as an online optimizer, and it is easier to maintain.

Keywords: Heat exchanger networks, Self-optimizing control, Real-time optimization, Jäschke Temperature

1. Introduction

Energy costs contribute a large portion of the total operating costs in a refinery, and limited global resources and strong competition are forcing plant owners and operators to find ways of operating their plants close to the optimum. Often, as in the case presented here, optimizing the heat exchanger network of the preheating train of a crude oil unit not only makes the process more energy efficient, but also allows for an increased throughput, which directly translates to higher revenues.

For optimizing operation of such a process, there are two common approaches. In the first one, online optimization (Marlin and Hrymak, 1997), a model is repeatedly optimized online during plant operation, and the computed optimal inputs are implemented in the plant. Here the plant measurements are used to update model parameters, and are not directly used for control purposes. With the recent rise in computing power, this method has become more and more attractive, and is used increasingly in the process industries. However, it is still an expensive method because of the high costs of developing and maintaining a good process model.

A different approach is based on using a model off-line to find a good set of controlled variables, which when held constant at their setpoints, indirectly leads to near-optimal operation in spite of varying disturbances. This approach is followed e.g. in self-optimizing control (Skogestad, 2000), or when tracking the necessary conditions for optimality (Srinivasan et al., 2003). Previously, there existed only methods for systematically finding linear combinations of measurements as self-optimizing controlled variables (e.g. Alstad et al. (2009)). However, recently there has been some activity in finding controlled variables which are polynomial

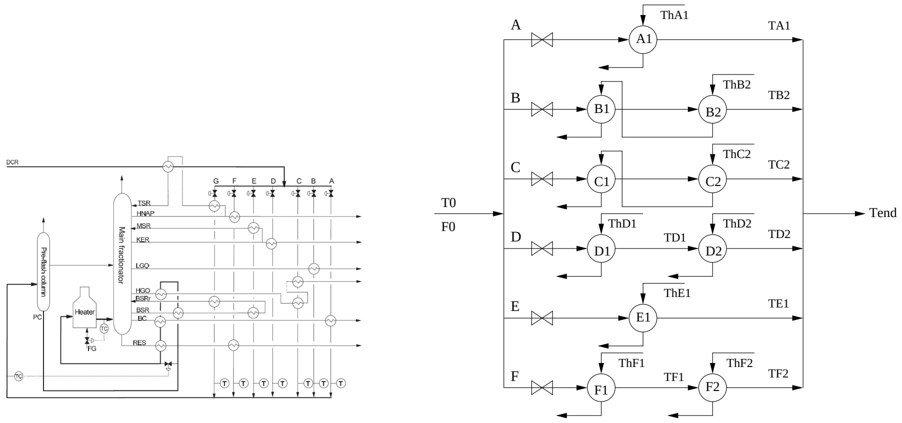

Figure 1. Schematic view of the preheating system of the Mongstad refinery

functions of measurements (Jäschke and Skogestad, 2012a). The polynomial structure adds more flexibility to optimally handle nonlinear plants. This approach has been successfully applied to heat exchanger networks with parallel flow paths, where the objective is to adjust the split such that the total heat transfer is maximized. It was found that under the assumption of the arithmetic mean temperature driving force, the "Jäschke Temperatures" of all branches must be equal under optimal operation. For a heat exchanger network with a cold feed at temperature T_0, which is split into two parallel branches with one heat exchanger each, the Jäschke Temperature T_J of a branch is defined as

$$T_J = \frac{(T - T_0)^2}{(T_h - T_0)}, \tag{1}$$

where T is the temperature of the cold stream after the exchanger, and T_h denotes inlet the temperature of the hot stream. The optimal control policy is thus to control the difference of the Jäschke Temperatures in all lines to zero. Although the Jäschke Temperatures were derived using the arithmetic mean temperature driving force, they have been found to give good performance when used on systems with a logarithmic mean temperature difference as driving force (Jäschke and Skogestad, 2014). The approach has been submitted for a patent (Jäschke and Skogestad, 2012b), and the objective of this paper is to present some results for an industrial size case study.

2. Process Description and Modelling

We apply the Jäschke Temperature approach to the preheating train of a model of the Mongstad refinery in Norway, Figure 1. Here a cold feed stream is split into parallel branches, which are heated using the hot product streams from the crude oil unit. Depending on the specifications, the product flow rates and temperatures from the crude unit will vary, and the optimization objective is to optimally adjust the split such that a maximum amount of heat is recovered. This minimizes the heat (and the fuel) required in the heater. Moreover, since the heater used to be the bottleneck of the process, optimizing the transferred heat directly translates into increased throughput and revenues. The hot and the cold path of the heat exchangers in the preheating train are modelled as a series of 10 ideally mixed tanks, which are exchanging heat with each other. This results in an approximation of the logarithmic mean temperature difference. No phase change takes place in the heat exchangers, and the heat transfer properties were fitted to data obtained from the Mongstad refinery. The heat capacities of the streams were fitted to temperature data from the plant. We assume that all branches have the same pressure drop, and that the flow F_i through the branch i is proportional to the valve opening z_i, such that $F_i = \frac{z_i}{z_A+z_B+z_C+z_D+z_E+z_F}F_0$ with $z_i \in [0, 1]$ for $i \in \{A,B,C,D,E,F\}$. A detailed description of the model is given in Leruth (2012).

3. Controlled variables for parallel heat exchanger systems

Consider the part of the preheating train shown on the right side of Figure 1. The optimization objective is to distribute the feed F_0 between the lines $A-F$ in such a way that the total heat transfer is maximized, i.e. the optimization problem can be written as

$$\max P = \sum_{i=A,\dots,F} Q_i \quad \text{subject to} \sum_{i=A,\dots,F} F_i = F_0, \tag{2}$$

where Q_i denotes the heat transferred in branch i (e.g $Q_B = Q_{B1} + Q_{B2}$), and F_i denotes the flow through the branch. Note that maximizing P is equivalent to maximizing T_{end}. For such a system of parallel heat exchangers, the optimality condition can be expressed in terms of the marginal costs $\frac{\partial Q_i}{\partial F_i}$ (e.g. Downs and Skogestad (2011)):

$$\frac{\partial Q_A}{\partial F_A} = \cdots = \frac{\partial Q_i}{\partial F_i} = \cdots = \frac{\partial Q_F}{\partial F_F}. \tag{3}$$

If the marginal costs $\frac{\partial Q_i}{\partial F_i}$ could be measured, then one could easily adjust the split such that the marginal costs are equal for all branches. However, in practice the marginal costs are not measured, as they are functions of unmeasured disturbances and parameters, such as heat capacities, stream temperatures and heat transfer properties UA. Instead of estimating all unknown parameters to be able to evaluate the marginal costs online, Jäschke and Skogestad (2014) have derived a simple approximation of the marginal costs in terms of temperatures only.

To simplify notation, we define the "shifted temperature" ΔT, where the Δ-operator denotes a shift in the reference temperature to the feed stream temperature T_0. For example, the shifted temperature of the exit temperature of stream A is $\Delta T_A = T_A - T_0$. The shifted temperatures of the other streams are calculated similarly. Using the shifted temperatures, the marginal costs are approximated by the Jäschke Temperature, which is defined for a line with N heat exchangers with N hot streams as

$$T_J = \sum_{j=1}^{N} a_j, \tag{4}$$

where the contributions corresponding to the individual heat exchangers $j = 1 \dots N$ are calculated as

$$a_j = \frac{(\Delta T_j - \Delta T_{j-1})(\Delta T_j + \Delta T_{j-1} - a_{j-1})}{\Delta T_{hj} - \Delta T_{j-1}} \quad \text{for } j \geq 1 \quad \text{with } a_0 = 0, \text{ and } \Delta T_0 = 0. \tag{5}$$

In the simple case of only one heat exchanger per line, as for line A in Figure 1, this formula reduces to

$$T_{J,A} = \frac{(T_{A1} - T_0)^2}{T_{h,A1} - T_0} = \frac{\Delta T_{A1}^2}{\Delta T_{h,A1}}. \tag{6}$$

The configuration on branch B and C, where there are two heat exchangers which are connected in counter-current configuration, can be considered as one large heat exchanger. Therefore, the Jäschke Temperatures for branch B is calculated as $T_{J,B} = \frac{\Delta T_{B2}}{\Delta T_{h,B2}}$, and the Jäschke

Table 1. Steady state simulation results

Outlet temperature	Optimized	Equal T_J
Branch A	228.45 °C	222.98 °C
Branch B	211.78 °C	214.69 °C
Branch C	217.49 °C	208.49 °C
Branch D	201.44 °C	202.41 °C
Branch E	200.39 °C	206.03 °C
Branch F	203.55 °C	202.93 °C
Total network T_{end}	207.79 °C	207.61 °C

Temperature for branch C is calculated in the same way. When two heat exchangers on a line are connected to different hot streams, as in line D, the Jäschke Temperature becomes

$$T_{J,D} = \frac{\Delta T_{D1}}{\Delta T_{h,D1}} + \frac{(\Delta T_{D2} - \Delta T_{D,1})(\Delta T_2 + \Delta T_{D1} - \frac{\Delta T_{D1}}{\Delta T_{h,D1}})}{\Delta T_{h,D2} - \Delta T_{D1}}, \tag{7}$$

and the Jäschke Temperature for line F is calculated the same way.

Surprisingly, as shown by Jäschke and Skogestad (2014), the Jäschke Temperatures correspond to the exact marginal costs, when the arithmetic mean temperature is assumed as temperature driving force in the heat exchangers. However, if the arithmetic mean temperature assumption does not hold, the expressions can be used as approximations of the marginal costs. The resulting near-optimal control policy is then to control the Jäschke Temperatures of all branches to equal values.

4. Results

4.1. Steady state simulation

In Table 1, we compare the optimized steady state operation point with the results obtained from our method. Controlling the Jäschke Temperatures to equal values gives slightly different end temperatures for the different branches, but we observe that the finally obtained end temperature after merging the branches again is very similar to the optimized end temperature. This indicates that the overall heat transfer in the different branches is almost identical to the optimized case. Because the Jäschke Temperatures are derived based on the arithmetic mean temperature assumption, our approach does not give the exact optimum. However, the performance is still very good. The reason for this is that the optimum in such a system is very flat, so that the stream split ratios can be off the optimal value, while still resulting in very close to optimal performance.

4.2. Dynamic simulations

To test the dynamic performance of our approach on the heat exchanger network, we consider three scenarios. In the first two scenarios we use a decentralized control structure, and in the third scenario we use model predictive control to control the Jäschke Temperatures to equal values. The temperature sensor dynamics are modelled as first order dynamics with a time constant of 5 seconds and a delay of 1 second.

In all three cases we use the difference between the Jäschke Temperature of branches $A-E$ and branch F, i.e. $c_i = T_{J,i} - T_{J,F}$ for $i = A,B,C,D,E$, as controlled variables. The reason all controlled variables are taken relative to T_{JF} is that branch F has the largest heat capacity, and thus we expect this to mitigate interactions when controlling the system.

4.2.1. Scenario 1 and 2: Decentralized control

The Jäschke Temperatures contain temperature measurements of inlet and outlet streams of the heat exchangers. A temperature change in an inlet stream, e.g. T_0, will have a direct effect on the value of the Jäschke Temperature. The effect of the exit temperature, however, will be on a slower time-scale, and therefore there will be competing dynamic effects in the disturbance response of the controlled variables. In Scenario 1 we will use the Jäschke Temperatures directly as controlled variables, while in Scenario 2, to mitigate undesired dynamic lead-lag effects on the response of the controlled variables, we add first order filters to the inlet temperature measurements. This ensures that all variables in the Jäschke Temperatures change at a similar rate, and avoids direct feed-forward of temperature disturbances from the feed streams to the controlled variables. Overall we expect this to results in smoother operation.

4.2.2. Scenario 3: Model predictive control (MPC)

Since the system is interactive, we also try using model predictive control to control the Jäschke Temperatures to equal values. The MPC was implemented using the Matlab™ and the model predictive control toolbox (Bemporad et al., 2012). We used a sample time of 60 seconds, which corresponds to the residence time in the smallest heat exchanger, and the prediction horizon was set to 10. The control horizon was set to 1 sample time, which is quite typical for many industrial MPC implementations and results in little computation time. Note that the MPC does not work on filtered incoming temperature measurements, because we expect the MPC to handle the lead-lag effects.

4.2.3. Results

All three approaches keep the controlled variables at their setpoints, and the performance looks quite similar. In the top of Figure 2 we have plotted the end temperature (objective function to maximize). The steady state value is very close (<0.5 K) to the optimal value for the disturbances:

- At 5000 seconds step in feed temp (+10 °C)
- At 6000 seconds step in feed flowrate (-10 %)
- At 7000 seconds step in hot stream inlet temperature branch C (-10 °C)
- At 8000 seconds step in hot stream flow rate on branch E (-10 %)

All three control structures give excellent performance, as can be seen from the temperature profiles of the end temperature in Figure 2. For comparing the input usage, we show the flow rates to line D and F. Here we see that the unfiltered decentralized approach and the MPC give a more aggressive control action, while the filtered decentralized approach gives a smother, slower performance. The difference is, however, not reflected in the end temperature. From this point of view, it seems that the filtered decentralized control structure works best, because it does not require as much input usage as the other approaches. However, de-tuning the MPC controller may also result in smoother control action.

5. Conclusions

We have applied the Jäschke Temperature approach to a large heat exchanger network for preheating the feed stream of a crude oil unit. This resulted in a very simple control structure, which gave very close to optimal performance. The main advantage of our approach is that it requires no optimization at all. Neither off-line, to find the optimal nominal split, nor on-line, to re-optimize when disturbances occur.

Although the Jäschke Temperatures were derived using the arithmetic mean temperature, it is found that controlling them to equal values also gives good performance when this assumption

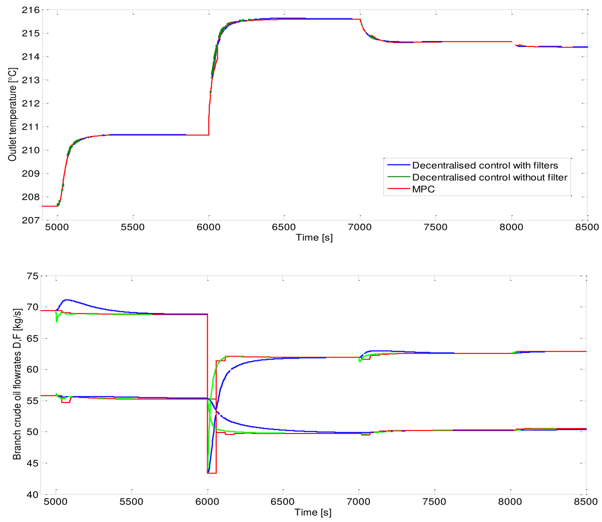

Figure 2. Comparison of control strategies. Top: Final outlet temperature T_{end}, Bottom: Flow rate through branches F and E

is not satisfied, and the logarithmic mean temperature is the driving force (or some approximation, as is the case in this work). The optima of these kind of systems are typically very flat, so if the split is not 100 % correct, the loss is still very small.

We applied a filter to mitigate the effects on different time scales. This resulted in an overall smoother control action. Note that the controllers need not be tuned aggressively, since because the goal is to optimize the energy consumption over a larger time-scale. From our simulations, it seems that using MPC and a decentralized control scheme give a practically identical performance in terms of the objective function (end temperature).

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