Self-Optimizing Control of a Two-Stage Refrigeration Cycle

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Abstract

The application of self-optimizing control theory to a two-stage refrigeration cycle was investigated. Defining the cost function as the economical trade-off between the power consumption and the evaporator outlet temperatures, it was found that the optimal point of operation leaves two unconstrained degrees of freedom for implementing a self-optimizing control structure. We consider two cases: (1) where the self-optimizing control structure is designed to optimally reject only physical process disturbances, and (2) where the control structure in addition handles changes in the economic parameters of the cost function. The control structure is able to keep the process close to optimal despite disturbances and changes in the product prices, and thus makes a supervisory real-time optimization (RTO) layer unnecessary.

Keywords: Self-optimizing control; refrigeration cycle; economically optimal operation;

1. INTRODUCTION

In recent years there has been an increased focus on improving energy efficiency and profitability in industry. Especially in large processes such as in the petrochemical industry, there are substantial potentials for savings due to the large power consumption. Multi-stage refrigeration cycles are large consumers of energy, so their optimal operation is an important topic of research.

In the presence of disturbances, implementation errors and changing operating conditions, the optimal operation of a process plant becomes non-trivial. One method for achieving optimal operation at all times is economic model predictive control (EMPC) (Ellis et al., 2014). Unfortunately, this method can be quite costly since it is based on the repeated optimization of a control trajectory over a prediction horizon. Depending on the complexity of the model, this dynamic optimization can be very computationally intensive and expensive to maintain. MPC of refrigeration cycles was investigated by Larsen (2006) and Leducq et al. (2006). A lot of research has been done on the field of EMPC of supermarket refrigeration systems, see for instance Larsen et al. (2007); Sarabia et al. (2007); Hovgaard et al. (2012) and the therein included references. The disadvantage of a model predictive control approach is that it requires a good model of the process, and that the computation time might be prohibitive.

A much simpler approach is to use a simple control structure to keep a carefully selected controlled variable at a constant set-point. This concept was introduced in Skogestad (2000) and coined "self-optimizing control". More precisely: "Self-optimizing control is when we can achieve an acceptable loss with constant set-point values for the controlled variables (without the need to re-optimize when disturbances occur)." Skogestad (2000) The self-optimizing controlled variables are often selected as either single measurements or linear combinations of measurements, which are usually controlled by simple PI or PID controllers.

Optimal operation of simple refrigeration cycles without MPC was studied by Jensen and Skogestad (2007a,b), who propose to use a feedback controller to keep a linear combination of two measurements, the high pressure and a temperature, constant. They determine the optimal combination of the measurements using the extended null space method (Alstad and Skogestad, 2007). Larsen et al. (2003) propose a similar strategy based on using a cascade formulation with the outer loop calculating the setpoint for the condenser pressure slave controller. Both Jensen and Larsen consider different variations of a single-stage layout.

The contributions of this paper are as follows: We design a self-optimizing control structure for a two-stage refrigeration cycle to ensure the optimal operation. We thereby generalize the results suggested by Jensen and Skogestad (2007b) by including all plant measurements rather than just pressure and temperature measurements. We also apply a branch and bound algorithm (Kariwala and Cao, 2009) to find the optimal subset of measurements that minimize the loss. Then we include measurements of cost function parameters (prices), and thereby show how selfoptimizing control can be used to ensure optimal operation when the prices change.

The paper is organized as follows. In Section 2, a brief overview of selected results from self-optimizing control theory is presented. In Section 3, the model of the twostage refrigeration cycle are presented. Two cases are studied. The first case results in a self-optimizing control structure with five plant measurements. The second case results in a self-optimizing control structure with measurements of the economic parameters from the cost function in addition to the five plant measurements. Simulation results are presented in Section 3 and Section 5. Finally, the conclusion is given in Section 6.

2. SELF-OPTIMIZING CONTROL

In this section, a short overview of self-optimizing control (SOC) is given for reader convenience. For more details, the reader is referred to Alstad et al. (2009).

Definition of optimal operation

After satisfying the active constraints, optimal operation can be formulated as an unconstrained optimization problem (Skogestad, 2000)

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

where J denotes the objective function. The optimal inputs **u** in the presence of disturbances **d** are calculated by a feedback control structure. It is useful for designing the control structure to work with the loss instead of using the cost directly (Halvorsen et al., 2003). The loss is defined as

$$L(\mathbf{u}, \mathbf{d}) = J(\mathbf{u}, \mathbf{d}) - J^{\text{opt}}(\mathbf{d}), \qquad (2)$$

where J^{opt} denotes the optimal cost for a given disturbance.

Exact local method

Since $J(\mathbf{d})$ is constant for a given disturbance, an equivalent optimization problem can be defined to replace Equation 1

$$\min \quad L(\mathbf{u}, \mathbf{d}). \tag{3}$$

The controlled variable \mathbf{c} in the feedback controller is chosen as a linear combination of measurements \mathbf{y}

$$\mathbf{c} = \mathbf{H}\mathbf{y}.\tag{4}$$

The matrix **H** is also called the measurement combination matrix. The goal of SOC is to select **c** such that the loss L in Equation 3 is minimized.

The exact local method (Alstad et al., 2009) is a method for finding \mathbf{H} which is based on a quadratic approximation of the loss and a linearized model for the measurements

$$\mathbf{y} = \mathbf{G}^{\mathbf{y}}\mathbf{u} + \mathbf{G}_{\mathbf{d}}^{\mathbf{y}}\mathbf{d} + \mathbf{n}^{\mathbf{y}}.$$
 (5)

Here, $\mathbf{G}^{\mathbf{y}}$ and $\mathbf{G}_{\mathbf{d}}^{\mathbf{y}}$ are the gain matrices from \mathbf{u} to \mathbf{y} and \mathbf{d} to \mathbf{y} , respectively. The variable $\mathbf{n}^{\mathbf{y}}$ denotes Gaussian noise on the measurements.

Scaled variables are introduced, such that

$$\mathbf{d} = \mathbf{W}_{\mathbf{d}} \mathbf{d}' \tag{6}$$

and

$$\mathbf{u} = \mathbf{W}_{\mathbf{n}^{\mathbf{y}}} \mathbf{n}^{\mathbf{y}'}.$$
 (7)

 \mathbf{d}' and $\mathbf{n^{y'}}$ are normally distributed with zero mean and unit variance. It is shown by Kariwala et al. (2008) that the average local loss for normally distributed noise and disturbances is given by

$$L_{avg} = \frac{1}{2} \left\| \left[\mathbf{J}_{\mathbf{u}\mathbf{u}}^{1/2} \left(\mathbf{H}\mathbf{G}^{\mathbf{y}} \right)^{-1} \mathbf{H}\mathbf{Y} \right] \right\|_{F}^{2}, \qquad (8)$$

where $\left\|\cdot\right\|_{F}$ denotes the Frobenius norm and

$$\mathbf{Y} = \begin{bmatrix} \mathbf{F} \mathbf{W}_{\mathbf{d}} & \mathbf{W}_{\mathbf{n}^{\mathbf{y}}} \end{bmatrix}.$$
(9)

Here, $\mathbf{F} = \frac{d\mathbf{y}^{\text{opt}}}{d\mathbf{d}}$ denotes the optimal sensitivity matrix.

Subsequently, the combination matrix that minimizes the average loss from (8) is given by the following expression.

$$\min_{\mathbf{H}} = \left\| \mathbf{J}_{\mathbf{u}\mathbf{u}}^{1/2} \left(\mathbf{H}\mathbf{G}^{\mathbf{y}} \right)^{-1} \mathbf{H}\mathbf{Y} \right\|_{F}.$$
 (10)

It can be shown that an analytical solution of (10) is (Yelchuru and Skogestad, 2010)

$$\mathbf{H}^{\mathsf{T}} = \left(\mathbf{Y}\mathbf{Y}^{\mathsf{T}}\right)^{-1}\mathbf{G}^{\mathsf{y}}.$$
 (11)

3. PROCESS DESCRIPTION

The model studied in this work is based on the twostage refrigeration cycle described by Asmar (1991). A full description of the model used in this work can be found in Verheyleweghen (2015). The process is based on a similar refrigeration cycle that is currently being operated in a petrochemical plant. A schematic of the process can be seen in Figure 1.



Figure 1. Process diagram of the refrigeration cycle. Key process variables are shown in blue, disturbances are shown in green and manipulated variables are shown in red.

The process is a two-stage refrigeration cycle with twostage throttling. Ethylene is used as the working fluid. The two compressor models are based on compressor curves, relating the compressor head, the suction volumetric flow rate and the compressor speed. A variable speed steam turbine drives the compressors, which are connected to the steam turbine through a common drive shaft. For simplicity, it is assumed that mechanical and thermal heat losses are negligible, so that the energy consumption of the compressors is equal to the enthalpy difference of the refrigerant from inlet to outlet. Interstage injection of saturated refrigerant increases the energy efficiency by reducing the load in the low pressure evaporator and by reducing the overheat into the second compressor (Granryd, 2009). The injection of saturated vapor can be adjusted by manipulating the control value u_1 .

Heat is removed from the system at three different temperatures. The majority of the heat is removed in a kettle reboiler at low pressure (LP) and low temperature. The pressure in this vessel is approximately 1 bar. At intermediate pressure (IP), heat is removed in a flash evaporator at a higher temperature. The pressure in this vessel is around 4 bar. The LP evaporator is approximately ten times larger than the IP evaporator. The distribution of gas and liquid in the two evaporators can be shifted by adjusting the control values u_1 and u_2 . In both evaporators the process streams exchange heat with the refrigerant through coiled pipes. It is ensured that the heating coils are always fully submerged in the liquid by constraining the levels in the tank. The heat transfer coefficient and the heat transfer area are therefore assumed to remain constant at all times. The compressed refrigerant is condensed in an air-cooled condenser. The condensate is collected in a receiver vessel which also acts as a buffer tank against disturbances and helps to ensure constant operating conditions in the evaporators and the compressors. The large size of the receiver introduces a large capacity to the cycle. This is especially noticeable for temperature (and consequently also saturation pressure) measurements, which take a very long time to reach a new steady-state value after a step change.

The thermodynamic states of the refrigerant are calculated using polynomial approximations of the Helmholtz equations of state calculated by the AllProps software (Lemmon et al., 1994).

The complete process model is a semi-explicit DAE system with six differential equations and ten algebraic equations.

3.1 Definition of the cost function

The objective of the optimization is to find the optimal economic trade-off between the energy consumption of the cooling cycle and the recovery of valuable molecules on the process side. The recovery is favored by low outlet temperatures from the evaporators. The cost function can be written as

$$J = \alpha W_{tot} + \beta T_1^{out} + \gamma T_2^{out}.$$
 (12)

Here, α , β and γ are the weighting parameters (prices). A large energy cost α causes the optimizer to prioritize minimization of W_{tot} , whereas a high value of the recovered molecules causes the optimizer to prioritize the minimization of the outlet temperatures T_1^{out} and T_2^{out} .

Since the process stream entering the LP evaporator has a lower temperature and a larger mass flow rate than the process stream entering the IP evaporator, β is chosen much larger than γ . We assume that

$$\begin{aligned} \alpha &= 0.1 \, \textcircled{K} \text{kWh} \\ \beta &= 12 \, \textcircled{K} \cdot \text{h} \end{aligned}$$

$$\gamma &= 0.1 \, \textcircled{K} \cdot \text{h}. \end{aligned}$$

$$(13)$$

As a first case, we assume the price parameters are constant. Due to fluctuations in the economic conditions, this may not be the case in practice. It is possible to use real-time optimization to include the effect of changes in α , β and γ . Alternatively, one can include measurements of these parameters in the controller set-point, which will be discussed in Case 2 in Section 5.

3.2 Nominal optimal solution

Given the model and the cost function from Equation 12, we define a nonlinear programming problem (NLP)

to find the optimal steady-state solution. The NLP was solved using the interior point algorithm in the fminconfunction in MATLAB. For this particular combination of cost function parameters and constraints, we found that the optimal solution had two unconstrained degrees of freedom after controlling the levels of the three pressure vessels, in accordance with the rules for inventory control defined by Aske and Skogestad (2009). In particular, u_2 and u_3 are used to control the levels in the LP evaporator and in the IP evaporator, respectively. Furthermore, it is found that the constraint on the coolant flow u_3 is always active on the upper bound, since no cost is associated with it. The two unconstrained degrees of freedom are the turbine speed u_{ℓ} and the value opening u_{1} . Both u_{ℓ} and u_1 are approximately half open at the optimal solution, though it is observed that the constraint region in which u_1 is unconstrained is relatively narrow. The nominal cost is $J = 2821 \in /h$.

In the following sections, two cases are considered. In Case 1, a self-optimizing control structure which uses only plant measurements is designed. In Case 2, measurements of the parameters α , β and γ are considered in addition to the plant measurements.

4. CASE ONE - REGULAR SELF-OPTIMIZING CONTROL WITHOUT MEASUREMENTS OF ECONOMIC PARAMETERS

4.1 Optimal selection of measurements

Using all available measurements in the calculation of the combination matrix \mathbf{H} would give the best possible control. However, this is not a viable strategy in practice, since each added sensor increases the overall chance of failure of the control structure. Structural complexity and the increased investment cost and complexity of the control structure also advise against excessive use of measurements. For these reasons, the number of measurements used in \mathbf{H} should be kept to a minimum. Heuristics can give a good indication of which measurements to include, but this approach requires system knowledge and is not feasible when the system is complex. In such a case, the best subset of measurements can be determined using the branch and bound algorithm proposed by Kariwala and Cao (2009).

For the studied process, only temperature-, pressure- and flow measurements correspond to real, measurable entities. From this potential set of 25 measurements, the branch and bound algorithm is used to determine the combination of five measurements which give the lowest loss. For Case 1, the five best measurements selected by the branch and bound algorithm are

$$\mathbf{y_1} = \begin{bmatrix} T_{dis} \ P_1 \ T_1^{out} \ F_1 \ F_3 \end{bmatrix}^{\mathsf{T}}.$$
 (14)

4.2 Optimality of controlled variables

A self-optimizing control structure is implemented with the remaining two unconstrained degrees of freedom. The scaling matrix $\mathbf{W}_{\mathbf{n}^{\mathbf{y}}}$ is constructed assuming that the variance of each measurement is equal to 1% of the nominal value. For temperature measurements, 0.5 K is used. The expected disturbance vector is assumed to be

$$\mathbf{d} = \begin{bmatrix} T_1^{in} & T_2^{in} & T_3^{in} & F_{p1} & F_{p2} \end{bmatrix}^{\mathsf{T}}, \tag{15}$$

Table 1. Case 1: Steady-state losses for selfoptimizing control and constant input policy for selected disturbances.

Variable	Disturbance	Steady-state loss $[\notin/h]$ Self-optimizing Constant inputs		
$ \begin{array}{c} \hline T_{1}^{in} \\ T_{2}^{in} \\ T_{3}^{in} \\ F_{p1} \\ F_{p2} \end{array} $	$+3K +3K +3K +10W K^{-1} +3W K^{-1}$	$\begin{array}{c} 0.340\cdot 10^{-2}\\ 0.076\cdot 10^{-2}\\ 0.020\cdot 10^{-2}\\ 17.146\cdot 10^{-2}\\ 0.190\cdot 10^{-2} \end{array}$	$\begin{array}{c} 15.114\cdot 10^{-2}\\ 0.018\cdot 10^{-2}\\ 3.424\cdot 10^{-2}\\ 29.366\cdot 10^{-2}\\ 0.208\cdot 10^{-2} \end{array}$	

being the inlet temperatures to the LP evaporator, the inlet temperature to the IP evaporator and the inlet temperature of the air in the condenser, respectively. F_{p1} and F_{p2} , being the combined mass flow rate and heat capacity of the process inlet to the LP and IP evaporators respectively, are also treated as disturbances. The matrix $\mathbf{W}_{\mathbf{d}}$ is

$$\mathbf{W}_{\mathbf{d}} = \begin{bmatrix} 3 \, \mathrm{K} & 0 & 0 & 0 & 0 \\ 0 & 3 \, \mathrm{K} & 0 & 0 & 0 \\ 0 & 0 & 5 \, \mathrm{K} & 0 & 0 \\ 0 & 0 & 0 & 10 \, \mathrm{W/K} & 0 \\ 0 & 0 & 0 & 0 & 3 \, \mathrm{W/K} \end{bmatrix}.$$
(16)

For the five best measurements, the combination matrix \mathbf{H} is calculated using Equation 11 as

$$\mathbf{H} = \begin{bmatrix} 0.0063 & -6.4947 & 0.0076 & -2.4821 & 4.7882 \\ -0.0000 & 0.4243 & 0.0030 & 0.2204 & -0.3913 \end{bmatrix}.$$
(17)

The performance of the control structure is tested for a set of disturbances as shown in Table 1. The steady-state losses are compared to the losses from a constant-input policy. It can be seen that for some disturbances the losses are in fact higher for the controlled system. However, on average the closed-loop loss is significantly lower than the open-loop loss.

It is also observed that the losses are almost negligible compared to the value of the cost function. Indeed, simulations revealed that the cost function was very flat around the nominal point. This means that the process will result in a cost function value that is very close to optimal even when in an open-loop configuration. It does therefore not make a significant difference if the system is controlled using $\mathbf{c} = \mathbf{H}\mathbf{y}$ or if the unconstrained degrees of freedom are not used for control at all. In conclusion, with the given cost function, the self-optimizing control is achieved also without any control (open loop).

4.3 Dynamic simulation

The self-optimizing controller was implemented in two PID controllers. Based on analysis of the RGA, it was chosen to pair the compressor speed u_4 with c_1 and the valve opening u_1 with c_2 . The PID tunings are derived based on the SIMC rules (Skogestad, 2003). As can be seen from Figure 2, the resulting closed-loop control structure has a large time constant. The controller could have been be tuned more aggressively by choosing a smaller closed-loop time constant, but here it was chosen as recommended in Skogestad (2003), where the closed-loop time constant is set equal to the effective delay.



Figure 2. Case 1: Responses of the controlled variables $(\Delta c_1 \text{ and } \Delta c_2)$ and the manipulated variables $(u_4 \text{ and } u_1)$ to a -3 K step in T_1^{in} for open loop and closed loop. The final plot compares the loss for the open loop and the closed loop.

The dynamic performance of the system was tested by applying a step in the inlet temperature to the LP evaporator, T_1^{in} . The resulting open-loop and closed-loop responses can be seen in Figure 2. We see that although the process behaves quite differently in open-loop and in closed-loop, the cost function is hardly affected. The other previously mentioned disturbances were also applied to the system. The responses are very similar to those shown for a disturbance in T_1^{in} , so they are not included here.

From Figure 2 it can also be seen that it takes a relatively long time for the loss to stabilize after it has been disturbed, even though the controlled variable reaches its setpoint almost immediately. This behavior is due to the slow dynamics of the system. The slow dynamics are caused by the very large capacity of the HP receiver, and are an inherent property of this refrigeration cycle.

5. CASE TWO - INCLUDING MEASUREMENTS OF COST PARAMETERS (α, β, γ)

A second case is considered to study the possibility of including measurements of the cost parameters α , β and γ in the set-point of the self-optimizing controller.

The same process model and cost function as previously discussed in Section 3 are used, so the optimal steady-state solution is the same as for the first case.

Table 2. Case 2: Steady-state losses for sel	lf					
optimizing control and constant input polic	сy					
for selected disturbances.						

Variable	Disturbance	Steady-sta Self-optimizing	te loss [€/h] Constant inputs
T_{t}^{in}	+3K	$0.372 \cdot 10^{-2}$	$15.114 \cdot 10^{-2}$
T_{2}^{in}	+3K	$0.004 \cdot 10^{-2}$	$0.018 \cdot 10^{-2}$
$T_{3}^{\tilde{i}n}$	+3K	$0.091 \cdot 10^{-2}$	$3.424 \cdot 10^{-2}$
F_{p1}	$+10\mathrm{W}\mathrm{K}^{-1}$	$11.35 \cdot 10^{-2}$	$29.366 \cdot 10^{-2}$
F_{p2}	$+3WK^{-1}$	$0.103 \cdot 10^{-2}$	$0.208 \cdot 10^{-2}$
α	$+0.01 \in /kWh$	1.959	20.47
β	$+1.2 \in /(K \cdot h)$	1.206	18.71
γ	$+0.01 \in /(K \cdot h)$	0.017	0.017

5.1 Optimal selection of measurements

In Case 2, the parameters α , β and γ are included in the set of measurements **y**, the new measurement vector being

$$\mathbf{y^{aug}} = \begin{bmatrix} \mathbf{y} \\ \alpha \\ \beta \\ \gamma \end{bmatrix}. \tag{18}$$

Using

where

$$\mathbf{y^{aug}} = \mathbf{G^{y,aug}}\mathbf{u} + \mathbf{G_d^{y,aug}}\mathbf{d^{aug}},$$
 (19)

$$\mathbf{G}^{\mathbf{y},\mathbf{aug}} = \begin{bmatrix} \mathbf{G}^{\mathbf{y}} \\ \mathbf{0} \end{bmatrix}$$
(20)

and

$$\mathbf{G}_{\mathbf{d}}^{\mathbf{y},\mathbf{aug}} = \begin{bmatrix} \mathbf{G}_{\mathbf{d}}^{\mathbf{y}} \\ \mathbf{I} \end{bmatrix}, \qquad (21)$$

the previously described approach for selecting ${\bf H}$ is applied to find a new controlled variable

$$\mathbf{c} = \mathbf{H}^{\mathbf{aug}} \mathbf{y}^{\mathbf{aug}}.$$
 (22)

This way, the control structure can react to changes in the electricity prices and the prices of the products immediately, without being dependent on an overlying real-time optimization layer. A similar idea is discussed by Jäschke and Skogestad (2011). The control structure will give optimal operation of the plant in spite of random price fluctuations. We assume that α , β and γ are known exactly, meaning that there are no measurement errors. The best subset of measurements is again found using the branch and bound algorithm. It was found that the best subset of eight measurements is

$$\mathbf{y_2} = \begin{bmatrix} u_1 & P_1 & P_3 & T_1^{out} & F_4 & F_7 & \alpha & \beta \end{bmatrix}^{\mathsf{T}}.$$
 (23)

It can be seen that the branch and bound algorithm does not give a set of measurements including all three economic parameters. γ is not included because the benefit from being able to control T_1^{out} more accurately far outweighs the drawback of having no information about the price of T_2^{out} . Consequently the control structure will not be able to react to changes in the price of the process stream in the IP evaporator, but they will not impact the cost anyway significantly, anyway.

The combination matrix $\mathbf{H^{aug}}$ is calculated from Equation 11



Figure 3. Case 2: Responses of the controlled variables $(\Delta c_1 \text{ and } \Delta c_2)$ and the manipulated variables $(u_4 \text{ and } u_1)$ to a step α_1 to α_2 for open loop and closed loop. The final plot compares the loss in the cost function for the open loop and the closed loop.

$$\mathbf{H^{aug}} = \begin{bmatrix} -5.4431 & 0.4448 \\ -6.9398 & 0.5136 \\ -0.2496 & 0.0218 \\ 0.0009 & 0.0002 \\ 4.0947 & -0.3249 \\ 1.3960 & -0.1061 \\ 0.0554 & 0.0096 \\ -0.0017 & 0.0000 \end{bmatrix}^{\prime} .$$
(24)

The steady-state losses for various disturbances can be seen in Table 2. It is observed that the self-optimizing control structure consistently outperforms the constant input policy. The control structure achieves comparable losses to the one proposed for Case 1. It is interesting to note that the changes in α , β and γ cause losses which are several orders of magnitude larger than the physical process disturbances. The self-optimizing control structure is able to reduce the losses significantly, except for changes in γ , since no measurement of γ is included in **c**.

The closed loop response to a +10% step in the energy price α is shown in Figure 3.

The self-optimizing control structure is able to react to changes in the economic parameters. Again, it is observed that the slow dynamics of the system cause the loss to very slowly reach a new steady state value. After approximately 7 minutes the closed-loop self-optimizing control structure starts outperforming the open-loop system.

6. CONCLUSION

In this paper we investigated the possibilities of applying self-optimizing control to a two-stage refrigeration cycle. Since the cost function is formulated to give a tradeoff between energy consumption and evaporator outlet temperature, it was found that the optimal point of operation leaves the compressor speed u_4 unconstrained. In addition, it was found that the valve opening u_1 remained unconstrained. Using the two degrees of freedom, a self-optimizing control structure was implemented.

It was found that the self-optimizing control structure does decrease the deviation from optimal operating conditions when disturbed. However, the decrease in observed loss is very small, mainly due to the flatness of the cost surface. This means that self-optimizing control is also achieved in open-loop operation.

More promising were the results from the second case, in which it was shown that self-optimizing control can include economic measurements to maintain optimal operation under price fluctuations. It was found that the steadystate loss can be significantly reduced. Consequently, selfoptimizing control can be a viable alternative to supervisory real-time optimization.

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