An industrial and academic perspective on plantwide control

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The purpose of this paper is to stress the importance of selecting the right plantwide control structure and the need for a formalized approach that can encompass the many issues that arise in plantwide control design. Since the concept of process control design based on a holistic view of the process came about, the variety of procedures and approaches to the design problem has illustrated the difficulty of a unified approach. Using examples, the need and advantages of using a systematic approach based on considering the plant economics are highlighted. The examples deal with disturbance rejection, throughput maximization and economic optimization of plants consisting of parallel units.

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1. Introduction

Industry uses a variety of approaches to accomplish plantwide control design. The range of tools used spans from engineering judgment to the applications of complex model based algorithms. Over the last 40 years the field of research in this area has attacked this design problem on various levels. Larsson and Skogestad (2000) provide a good review of the various approaches. Design heuristics based on experience, design rules based on case studies, algorithms for objective function minimization, etc. have all contributed to the improvement of how designs can be accomplished (e.g., Chen & McAvoy, 2003; Douglas, 1988; Downs, 1992; Konda, Rangaiah, & Krishnaswamy, 2005; Kookos & Perkins, 2002; Luyben, Tyreus, & Luyben, 1998; Narraway & Perkins, 1993; Skogestad, 2004; Vashinder & Hoo 2003; Ward, Mellichamp, & Doherty, 2006; Zheng, Mahajanam, & Douglas, 1999). However, the complex nature of the problem and the various depths to which it needs to be solved have resulted in a design procedure that is difficult to piece together from the various approaches that have been put forth. This is not a new issue and almost 20 years ago the “Tennessee Eastman challenge problem” (Downs & Vogel, 1993) was put forward so that various approaches could be tested against each other. Nevertheless, today in industry, much of the research in this area has still not gained sufficient acceptance to have a profound influence. The purpose of this paper is to stress the need for a formalized yet simple approach that can encompass the many levels that arise in plantwide control design.

In Section 2, industrial aspects of plantwide control design are discussed and two examples illustrate how industry has approached the plantwide control problem. Although the final control structure may be good, the approach and criteria to arrive at it may vary. This points to a need for a more formal procedure which is presented in Section 3. In Section 4, the inclusion of plantwide economic variables is presented and illustrated in Section 5. The paper concludes that the formal approach presented is a step in the direction of helping to organize the design procedure for plantwide control. This paper also illustrates the application of the formal procedure to more complex examples that illustrate that plantwide design involves many issues and one-criterion approaches may not be sufficient.

2. Status in industry

The traditional approach for Eastman for designing process control strategies for chemical plants has been to set production rates using the process feed rates and then to design automatic control systems around each unit operation sequentially through the process. For processes with significant in-process inventory, including buffer tanks, and limited recycle, this approach can be used successfully. However, as processes become more complex and at the same time have less in-process inventory, the design of a plant-wide control strategy becomes a more important part of the overall process control design problem. The interrelation of the plant-wide control strategy with the process chemistry and economics requires both control theory and also process knowledge. It has become apparent that the design of plant-wide control strategies involves not only the development and...
application of process control theory but also, in a more fundamen-
tal sense, the development of a methodology one uses to approach
the plant-wide control problem.

While we usually think about material balance and energy bal-
ance equations applying to a unit operation, they also apply to
whole processes and to entire chemical complexes. The time it
takes to accumulate and deplete inventories may be longer for
large processes or chemical complexes, but the laws of accumula-
tion and depletion of material hold nonetheless. Whereas for a
steady-state process, we assume the rate of accumulation of each
component to be zero, the fact that the control system must ensure
that to be the case is often overlooked. The manipulation of flows,
utilities, and the readjustment of process operating conditions
to maintain a balance of material and energy entering and leaving
an entire process are some of the overriding priorities for the con-
tral system (Buckley, 1964). The material balance must be main-
tained not only from an overall viewpoint but also for each
component in the system.

While traditional control theory can be used to approach the
control problem as, “Given a process described by a model of the
form...,” the plant-wide control problem requires much more in
the development of the problem statement itself. It is not intuit-
ively obvious at the outset what the underlying control problems
are—much less how they should be solved. As researchers have be-
gun to explore the plant-wide control area, the application of
methods and techniques as applied to case studies (e.g., Luyben
et al., 1998) has elucidated issues that are difficult to quantify
and are in need of further discussion and research.

Despite the ever-increasing incentive, segregation of the pro-
cess design and control tasks is still common. Two contributing
factors to this segregation are: (1) the difficulty of chang-
ing from the historical approach of fixing the process design before the con-
trol engineer becomes involved, and (2) the difference in
the thought patterns of design and control engineers. In addition it
can be costly and time consuming to address controllability and
operability in a rigorous way at the design stage. The common
notion is that process economics are solely determined by the stea-
dy-state process design. While the nominal steady-state design
point is very important, it loses its distinction if one is unable to
maintain plant operation at the desired operating point. Design
decisions are often based on a nominal steady-state analysis with
little consideration of disturbances, changes in active constraints,
controllability, process and product variability, or plant-wide con-
trol issues. The basic thought pattern in the design stage usually
follows the form, “Given these conditions, create a design to per-
form this function” (design function), as opposed to, “Given this
design, how well will it perform its intended function?” (rating
question). As existing plants are pushed to produce greater
throughputs, an additional question becomes important, “Given this
plant, how can I maximize profit?” (optimization question).

In summary, we need a plantwide control system that implemen-
tars in practice the operation envisioned at the steady state design
stage. There is a link between process design and control here, in
that the process design team should, in addition to the plant design
and its nominal operating data, provide optimal operating data
also for expected future changes, including the expected location
of the bottleneck when the throughput increases.

Current industrial practice is usually focused on unit operation
control. This viewpoint emanates from the overriding issue of reli-
able operation. These unit control strategies are simple and under-
standable by operators and engineers alike and lead to operations
that when “sick” can usually be healed without the capabilities of
experts. This approach has worked reasonably well for many years.
Furthermore, the high costs of building new facilities have led to
more retrofits and plants producing products that they were not
designed to produce. As plants are campaigned to produce a wider
variety of product specifications, control strategies that are simple
and perhaps applicable to many different operating points are
strongly desirable.

This current design practice is being challenged as process eco-
conomics drive toward fewer new designs and more operation of
existing facilities in new ways. Techniques for plant wide process
control design are needed (1) that result in processes that are oper-
ated in near optimal fashion while not employing complex control
technology, for example, real-time optimization (RTO), and (2) that
do not require the care and feeding of control experts. Several
approaches that address the attainment of optimal operation of
plants while not requiring implementation of complex, perhaps
difficult to understand control systems, have emerged. Two of
these, self optimizing control design (Skogestad, 2000) and opera-
tional strategies based on process chemistry (Ward, Mellichamp,
& Doherty, 2004; Ward et al., 2006) have found particular appeal at
Eastman.

The importance of being able to discriminate how process vari-
ables need to behave to achieve optimal operation is fundamental
when designing plantwide strategies. Often the underlying unit
operation strategies can be kept simple and usually single-input
single-output (SISO) while the overall plant wide strategy is opti-
mizing plant operation in a more natural fashion. This approach
has a wide appeal when plant reliability and control system under-
standability are required. Each of these approaches builds into the
control system a natural “self-optimizing” that is part of a normal
operation. Contrasted with the centralized approach (e.g., RTO) of
using models to determine an optimum and then driving a process
to that optimum point, “self-optimizing” strategies designed in
from the bottom, provide simplicity, robustness and reliability.

From the start-up the primary objective for a new plant is to
achieve nameplate (nominal) capacity in a reliable and predictable
way. Often the need for optimization of plant operations comes
after the facility has been operational for a few years. By this time
top-down optimization strategies can be implemented, provided
the plant has a good regulatory control system. If the optimization
strategy is counterintuitive, then operator understanding can suf-
f er. Most control engineers have experienced the difficulty of keep-
ing in service control strategies that, while driving the process to
the correct economic conditions, does so in an unusual or difficult
to understand fashion.

The importance of having plantwide control strategies that are
optimizing in a natural, fundamental way can have long term
effects. Operator training and understanding during the early years
of plant operation sets thought patterns for years to come. When
the need for plant optimization arises, the basic building blocks
of how the control system automatically drives plant operation
are in place. The process optimizer at this time may only have to
make small adjustments to a process that is close to optimum
already. The trick, of course, is that these strategies must be
basically simple and for the most part SISO. Our experience from
Eastman is that for plants where “self-optimizing” regulatory
control strategies have been built in from the beginning, we have
been successful with process optimization projects that have been
undertaken. On the other hand, for older processes which have
control strategies not designed with optimization in mind, we
may struggle for years working to gain operator acceptance to a
new strategy. Even the simple idea of setting process throughput
at a place other than the process feed can become a difficult
endeavor.

Example 1 (Changing the production throughput manipulator
TPM for an esterification plant). Eastman operates many processes
that have produced chemicals for over 50 years. Esterification chemis-
try is well known and has been a workhorse for the company.
Traditionally, units were designed with the process throughput set
at the feed to the process. Control systems consisted of pneumatic
gle single input/single output controllers that were difficult to change
ld and had a long operating history. As production rates increased
ver the years due to demand growth and incremental process
vement, the original plantwide strategy would become
n. A flowsheet of a typical esterification process, consisting of
reactor with a distillation column, followed by an extraction
column and a distillation column is shown in Fig. 1. The first
distillation column separates water, ester, and alcohol from
the unreacted acid. The extraction column washes the unreacted
alcohol from the ester product. The final distillation column
vms the remaining unreacted alcohol, which is recycled to
the extraction column. The flowsheet shows the original plant had
with the throughput manipulator (TPM) located at the reactor feed.

In the late ’70’s and early ’80’s Eastman benefited from imple-
menting a change in the TPM location on numerous plants. Early
adoption of this significant change was difficult because of (1) an
grained mindset toward needing process feeds constant, (2)
operator understanding of an “inventory-to-feed” strategy, and
(3) the difficulty of reversing the control decision using pneumatic
hardware. Today at Eastman, the notion of setting the TPM at a
location other than the process feeds is common and is driven by
variability propagation and ease of operation requirements. The
benefits of choosing the best location for the TPM have also
become realized in our capital design process.

For the esterification process the first change was to move the
TPM from the process feed rate to the distillate flow rate leaving
the first distillation column as shown in Fig. 2. This strategy
worked well for many years because many of the disturbances
entering the reactor were directed away from the more sensitive
extraction/distillation separation portion of the process.

Later, as the extraction step became the process bottleneck, it
became evident that its behavior as a function of organic feed rate
was very nonlinear. This nonlinearity stemmed from the fact that
increasing organic feed rate resulted in an increasing composition
of the alcohol taken from the extractor to the final distillation
column. The increase in distillate rate (recycle stream R in Fig. 2)
needed to remove the alcohol from the final product would aggra-
vate the situation by increasing the feed rate to the extractor.
The point at which the process would enter this “windup” varied with
the amount of unreacted alcohol reaching this part of the process.
This windup in the recycle loop is similar to Luyben’s “snowball ef-
fct” (Luyben, 1994), but the cause in our case is a limitation in
mass transfer rate whereas in Luyben’s case it is a limitation in
reaction rate. For this process, the windup condition usually took
12–24 h to get fully engaged. This made it difficult for operators
to confidently set the production rate. In addition, what may be a
maximum and stable rate today might result in the windup condi-
tion tomorrow. The outcome of this uncertainty resulted in opera-
tions setting a lower than optimum production rate to guarantee
process stability.

A further improvement in locating the TPM occurred when it
was relocated to be the feed to the extraction system (Fig. 3). Obvi-
ously, this eliminated variability from propagating to the extractor,
but more importantly, it resulted in a self regulating system that
avoids the windup should the operator set the TPM too high. In
particular, if the TPM is set too high and excess alcohol leaks to
the final distillation system, then less feed is drawn from the front
end of the process, and the extractor, while not at the optimum
feed rate, does remain stable. This situation is quite recoverable
by operators who note that production rates have fallen, and real-
ize that they have set the extractor feed rate too high. We found
that the operators were capable of optimizing the operation once
fear of setting the extractor feed too high was removed.

The strategy in Fig. 2, and in particular the original strategy in
Fig. 1, were unforgiving in that once the throughput was set too
high, it resulted in flooding in the extractor and distillation col-
umns and several hours of lost production. With the final control
strategy in Fig. 3, the ability to experiment with the throughput
without the penalty of passing this “point of no return”, gave

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**Fig. 1.** Esterification process. Original inventory control strategy with column 1
feed rate used as the TPM.

**Fig. 2.** Esterification process. Inventory control strategy with column 1 distillate
rate used as the TPM.

**Fig. 3.** Esterification process. Final inventory control strategy with extractor feed
rate used as the TPM.
operators confidence in the control system to recover if they ended up pushing rates too high, and made them operate the process closer to its maximum throughput.

The basis for relocating the TPM in Figs. 2 and 3, was mainly process insight as described above. However, it agrees with more general recommendations. First, note that the capacity of the extraction column is the bottleneck of the process, so locating the TPM here agrees with the rule of Skogestad (2004) of moving the TPM to the bottleneck unit. Second, note that the TPM is located inside the recycle system, so it agrees with Luyben’s rule (1994, 1997, 1998) of fixing a flow inside the recycle system. One justification for Luyben’s rule is that setting a flow in the recycle loop avoids the slow dynamics of the recycle system (e.g., Morud & Skogestad, 1996) that otherwise makes it difficult to have tight control, especially using manual control.

**Example 2** *(Control strategy for a liquid–liquid extraction process)*. During the control design phase, the engineer may chose from a variety of criteria (or rules) and the criterion chosen is usually based upon engineering judgement. The importance of the criterion choice is often not appreciated. The objective of this example is to illustrate the design criterion of propagating disturbances to insensitive location, which has been successfully used in many applications in Eastman. The resulting control strategy can then be compared with those obtained using a more methodical approach.

Consider the extraction process in Fig. 4 where acid is transferred from the water/acid feed \( F \) to the extract \( E \) by use of a solvent \( S \). The remaining water is the raffinate byproduct \( R \). Apart from maintaining stable operation, the main control objective is to have small variations in the extract product composition.

The total inventory is self-regulated by overflow of extract, but the interface level (component inventory) does not self regulate. How should this inventory be controlled? Two alternatives are shown in Fig. 5.

**Strategy I.** Let aqueous feed \( F \) control interface level (with constant outflow \( R \)).

**Strategy II.** Let aqueous outflow \( R \) control interface level (with constant feed \( F \)).

Both of these structures have been used for extraction control in various services including the example given here. Obviously, both structures work and give the same result if everything is constant (no disturbances). How do the two strategies differ when there are disturbances? To understand the difference we ask the question: “Where does the disturbance go?”

Let \( x \) denote the acid fraction, and consider variation (disturbance) in the acid feed fraction \( x_F \) by \( \pm 1\% \ (30 \pm 1\%) \). We would like that the resulting variation in the extract product to be reduced by at least a factor 3, that is, the variation in \( x_E \) should be less than \( \pm 0.33\% \). For strategy I, the resulting variation in the acid composition of the extract product \( (x_E) \) is \( \pm 0.856\% \ (21.4 \pm 0.856\%) \) and for strategy II it is reduced to \( \pm 0.506\% \ (21.4 \pm 0.506\%) \), which is still significantly higher that the desired variation. For details see the mass balances in Table 1. The mass balances were derived by assuming that we for the extract phase \( E \) have acid/water \( = 3 \) (equilibrium), and that the raffinate \( R \) is pure water (see Table 2).

In summary, for strategy I with \( R \) constant, the variation in \( x_E \) results in variations in the feed flow, \( F \), and in \( x_F \) (with gain 0.856), while for strategy II with \( F \) constant, the variation in \( x_F \) results in variations of the outlet flow, \( R \), and to a lesser extent in \( x_E \) (with gain 0.506). Strategy II is the preferred strategy of the two since the main objective is to have small variations in \( x_E \). This example illustrates how different inventory strategies may result in process variability being transferred to different parts of the process.

The criterion of propagating disturbances to insensitive locations gives good insight and has given good designs for many cases. However, for more complex problems and for less experienced engineers a more systematic approach is needed. We will discuss this below where we introduce control strategies III, IV and V.

**3. A plantwide control design procedure**

This section is largely based on the plantwide procedure of the second coauthor (Skogestad, 2004). No matter what approach we use, the following decisions need to be made when designing a plantwide control strategy:

**Decision 1.** What to control? Selection of controlled variables (CVs) to achieve

a. Good steady-state performance (economics), and
b. “Stable” operation with little dynamic drift (including selecting CVs related to inventories).

**Decision 2.** Where to set the production rate? Placement of throughput manipulator (TPM).

**Decision 3.** How to control the inventories? How to pair the loops? That is, selection of a control configuration that interconnects CVs and MVs.
Often in industrial practice all issues are considered simultaneously without making formal decisions that answer the above three questions. For the extraction process in Example 2 the need for good extract composition raised the question of how best to respond to using all degrees of freedom to satisfy active constraints. There will be a bottleneck somewhere in the plant, and should form the basis for the actual decisions in steps 3–7. A detailed analysis in steps 1 and 2 requires that one has available a steady-state model and that one performs optimizations using for the given plant design (”rating mode”) for various disturbances. As mentioned in Section 2, where we discussed the link between process design and process control, this should ideally be done at the design stage where the steady-state model is usually available. However, this is often not done in industrial practice, because the model used for design may not be suitable or available, the working relationship between the design and control functions may be weak, or there may not be time to perform this analysis.

Nevertheless, one should at least perform a simplified engineering version of steps 1, 2, and 3 where one thinks through the economics of the present and future operation with aim of using process insight to propose which variables to control, keep constant, from a steady-state economic point of view. In particular, a good engineer can often easily identify the “active constraints” that the control system should maintain. That is, where should one optimally stay at maximum or minimum values of flow, temperature, pressure, composition, etc?

Simplified step 1–3. Identify degrees of freedom and main disturbances. Based on process insight, select variables to keep constant (Decision 1a).

There have been many applications of the above design procedure, e.g., see Araujo, Govatsmark, and Skogestad (2007), but most of them on academic problems. There exist several other procedures for plantwide control (e.g., Luyben et al., 1998), but they focus mainly on the bottom-up part, and in particular on step 5. However, making good decisions in step 5 can be difficult without having first gone through the top-down plantwide economic analysis in steps 1–4.

Step 4 (location of TPM) was addressed in Example 1, and this issue is further discussed in the recent PhD thesis by Aske (2009); see also Aske, Strand, and Skogestad (2008).

The focus of the rest of this paper is on step 3 (economic CVs). In this respect it is important to notice that the best control structure may vary, and, depending on market conditions, there are two main modes of operation:

Mode I. Maximize efficiency (for a given throughput).

With a given throughput (production rate), the value of the products is usually known, and provided there are degrees of freedom left after satisfying the constraints (specifications), the economic objective is to minimize the use of utilities, maximizing raw material yield, and to minimize waste treatment costs. These and other issues that increase specific production costs are the same as maximizing the efficiency. As discussed in Section 2 on the industrial status, the control system for a new plant is usually set up to handle this mode of operation well.

Mode II. Maximize throughput (with production rate as a degree of freedom).

When market demand is good and product prices are high, the profit is maximized by running the plant at maximum throughput. In fact, the first thing that the operation people usually focus on after startup of a new plant is to increase throughput because the opportunities for extra profit in mode II are usually much larger than in mode I. In spite of this there is usually no effort during the design phase to design a control system that can operate at maximum throughput. Operation at maximum throughput usually corresponds to using all degrees of freedom to satisfy active constraints. There will be a bottleneck somewhere in the plant

### Table 1

<table>
<thead>
<tr>
<th>Feed, F</th>
<th>S</th>
<th>Extract, E</th>
<th>Raffinate, R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>I</td>
<td>II</td>
<td>III, IV</td>
</tr>
<tr>
<td>Water</td>
<td>70</td>
<td>70.568</td>
<td>69</td>
</tr>
<tr>
<td>Acid</td>
<td>30 (30%)</td>
<td>31.705 (31%)</td>
<td>31 (31%)</td>
</tr>
<tr>
<td>Solvent</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>102.273</td>
<td>100</td>
</tr>
</tbody>
</table>

#### Table 2

General mass balances for extraction process.

<table>
<thead>
<tr>
<th>Acid/water feed (F)</th>
<th>Solvent feed (S)</th>
<th>Extract product</th>
<th>Raffinate byproduct (R)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>F_W</td>
<td>F_S</td>
<td>F_E - F_S/3</td>
</tr>
<tr>
<td>Acid</td>
<td>F_A</td>
<td>F_A</td>
<td>0</td>
</tr>
<tr>
<td>Solvent</td>
<td>0</td>
<td>F_S</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>F = F_W + F_A</td>
<td>S + F_S</td>
<td>E = (4/3)F_A + F_S + R = F_W - F_A/3</td>
</tr>
</tbody>
</table>

* Acid/water = 3 in extract phase.
is important to maintain a constant product composition (thus need to decide on 1 'economic' CV). From process insight it to be given (mode I), which consumes another degree of freedom.

However, at steady state there are only 2 degrees of freedom because the interface level, which has no steady-state raffinate R. However, at steady state there are only 2 degrees of freedom.

Step 5. Structure of regulatory control layer (including inventory control). The TM location is important both for economic reasons in the context of utilizing the buildings (Abbott et al., 2008) and because (Busby, 1984; Perz & Georgakis, 1992). The throughput plant is typically located at the main feed, but could generally be anywhere in the process. Since the main feed was proposed as an intermediate (main feed strategy), the solvent level is the throughput manipulator (DeClerck, 2001). Indeed, this is the optimal location for this process because the regeneration of solvent is the capacity bottleneck.

We must next decide how to control the interface level. To avoid saturation of the MV, and this tells us that we should prefer the largest flow, which is the feed F. However, one should also consider the optimal location for this process because the regeneration of solvent is the capacity bottleneck.

**Decision 1**. The first inventory is self-regulated by overhead, but also the interface level between the two liquid phases must be controlled. Thus, CV1 = interface level.

We now want to apply the systematic plantwide procedure to the extraction example, where we previously used the design criterion that disturbances should be propagated to insensitive locations. Thus, for the extraction example, where we previously used the design criterion that disturbances should be propagated to insensitive locations.

The extract product flow (E) is on overflow, so there are 2 MVs that can be used for control: the two feed flows (F and R). However, one should also consider the optimal location for this process because the regeneration of solvent is the capacity bottleneck.

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**Step 2. Select location of throughput manipulator (TPM) (Decision 2).**

The TPM location is important both for economic reasons in the context of utilizing the buildings (Abbott et al., 2008) and because (Busby, 1984; Perz & Georgakis, 1992). The throughput plant is typically located at the main feed, but could generally be anywhere in the process. Since the main feed was proposed as an intermediate (main feed strategy), the solvent level is the throughput manipulator (DeClerck, 2001). Indeed, this is the optimal location for this process because the regeneration of solvent is the capacity bottleneck.

**Step 3. Identify degrees of freedom (MVs) and main controlled variables (CVs).**

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**Example 3** (Application of systematic design procedure to liquid extraction process in Example 2). The process is very simple and there are no degrees of freedom left for steady-state economic optimization once the specifications are satisfied. Thus, for the systematic procedure we use the simplified approach to insensitive locations.

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**Step 5. Structure of regulatory control layer (including inventory control).**

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**Step 6. Structure of supervisory control layer.**

As already discussed, the location of the TM for the crystallization plant in Example 1 agrees with this rule. We now want to apply the systematic plantwide procedure to the extraction example, where we previously used the design criterion that disturbances should be propagated to insensitive locations. Thus, for the extraction example, where we previously used the design criterion that disturbances should be propagated to insensitive locations.

**Step 7. Control structure in Example 2.**

The remaining MV F is used to control acid composition in the extract (CV2 = const). The final control structure shown in Fig. 6 is the same as strategy II with an additional composition loop to keep the extract composition constant.

**Step 8. Control strategy in Example 2.**

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**Step 9. Example 3 (Application of systematic design procedure to liquid extraction process in Example 2).** The process is very simple and there are no degrees of freedom left for steady-state economic optimization once the specifications are satisfied. Thus, for the systematic procedure we use the simplified approach to insensitive locations.

We now want to apply the systematic plantwide procedure to the extraction example, where we previously used the design criterion that disturbances should be propagated to insensitive locations. Thus, for the extraction example, where we previously used the design criterion that disturbances should be propagated to insensitive locations.

**Step 10. Example 3 (Application of systematic design procedure to liquid extraction process in Example 2).** The process is very simple and there are no degrees of freedom left for steady-state economic optimization once the specifications are satisfied. Thus, for the systematic procedure we use the simplified approach to insensitive locations.
that the composition of $E$ must remain constant (again assuming $S$ constant).

Strategy IV is a special case of a “self-optimizing” measurement combination, as discussed below. In fact, since we have $n_d = 1$ disturbance $(x_d)$ and $n_u = 1$ steady-state degrees of freedom, we have from the nullspace theorem (Alstad & Skogestad, 2007) that self-optimizing control can be obtained by controlling a combination of $n_u + n_d = 2$ independent measurements. The flows (MVs) $R$ and $F$ are here candidate “measurements”, so a possible controlled variable is $CV_1 = h_1 F + h_2 R$. In general the values for $h_1$ and $h_2$ can be found in a systematic manner using the nullspace theorem, and as we will shown later this yields $h_1 = 1$ and $h_2 = -1$ (strategy IV). For this particular example we arrive at the same result using process insight, but in general this may not be so easy and the systematic approach is preferable.

In strategy IV, the setpoint $(F - R)_e$ may be adjusted based on (infrequent) measurements of the product composition $x_E$. In particular, we will need to increase $(F - R)$ if the throughput increases. However, by process insight (or looking at the model equations) we have that all flows should be scaled by the throughput to keep $x_E$ constant, and this leads the improved strategy V.

**Strategy V**: Measure the solvent federate $S$ (measured disturbance) and keep the variable $CV_1 = (F - R)/S$ at a constant value, see Fig. 8. To correct for measurement errors, drift and other disturbances, the setpoint for $(F - R)/S$ may be adjusted based on (infrequent) measurements of the product composition $x_E$. Note that control strategy V is “self-optimizing” (giving constant product composition $x_E$) with respect to both disturbances in feed composition ($x_F$) and solvent federate ($S$), whereas control strategy IV only handles disturbances in feed composition ($x_F$). In the next section, we will show to find self-optimizing strategies in a systematic manner.

### 4. Selection of economic (primary) CVs

In the above example, we found that the relative flow difference $CV_1 = (F - R)/S$ is a good primary CV. How do we find good primary (economic) CVs in a systematic manner (step 3)?

We make the standard assumption here that a steady-state analysis is sufficient for studying the economics. The question is: How can we turn optimization into a setpoint problem? What should we control (CV) to get close-to-optimal operation (with minimum cost $J$)? The obvious CV is the gradient of the cost function, $J_u = df/du$, which should be zero at the optimum point, independent of disturbances. However, before we look at this and other ideas, let us look in a bit more detail in steps 1–3 in the proposed procedure for selecting CVs.

**Step 1. Define operational objectives (cost $J$) and constraints**

In many cases a simple economic cost is used:

$$\text{Profit} = -J = \text{value products} - \text{cost feeds} - \text{cost utilities (energy)}$$

Other operational issues, such as safety and environmental impact are usually formulated as constraints. For cases with good market conditions we often have a constrained optimum and the cost function can be simplified to $J = TP$ (mode II, maximum throughput).

Other cost functions are also possible. For example, consider the extraction process. Here, the optimum is to keep a constant product composition $x_E$, but we cannot control it directly because there is no online measurement. We therefore want to control something else that gives *indirect control* of the primary output (Hori, Skogestad, & Alstad, 2005). The cost function is then $J = (x_E - x_{E0})^2$.

**Step 2. Identify degrees of freedom and optimize operation for various disturbances**

One approach for optimization is to use a steady-state spreadsheet simulator, if available, and optimize the operation with respect to the degrees of freedom for various disturbances. However, this may be very time consuming and in many cases, simpler models and approaches may be used. Typical “disturbances” include feed composition, feed rate, reaction rate constants, surroundings, values of constraints and prices.

**Step 3. Select primary (economic) controlled variables**

The issue here is to select the primary (economic) controlled variables (CVs). That is, for what should we use the (steady-state) degrees of freedom? What should we control?

1. **Control active constraints.** The active constraints come out of the analysis in step 3 or may in some cases be identified based on physical insight. The active constraints should be selected as CVs because the optimum is not “flat” with respect to these variables. Thus, there is usually a significant economic penalty if we “back off” from the active constraints, so *tight control of the active constraints is usually desired*. Poor control makes it necessary to “back off” from the active constraint and this gives a loss. If a constrained optimization method is used for the optimization, then we can find the magnitude of the loss from the Lagrange multiplier $\lambda$, and we have Loss = $\lambda \cdot \text{backoff}$.

![Fig. 7. “Self-optimizing” control strategy for extraction process.](image1)

![Fig. 8. Improved “self-optimizing” control strategy for extraction process.](image2)
Specifically, in mode II the feed rate should be adjusted to keep the bottleneck unit operating at its active constraints. Any back-off from the active constraints will reduce the flow through the bottleneck unit and give a loss in feed flow (production) which can never be recovered.

1. Identify “self-optimizing” variables related to the (possibly) remaining unconstrained degrees of freedom. These are (seemingly) “magic” variables which when held constant result in close-to-optimal operation (with a small loss), in spite of the presence of disturbances. The term “magic” is used to signify that the choice may have a significant effect on the economics (loss), and that it is not generally obvious what a good choice is. A good self-optimizing variable should give a “flat” optimum, which means that tight control of these variables is usually not required (as opposed to the active constraints). Note that the different self-optimizing variables must be found for each region of active constraints.

There are two main possibilities for selecting self-optimizing CVs:

1. Select single measurements as CVs (however, it is difficult to find single measurements in a systematic manner, so one must often use the “brute force” approach).
2. Use measurements combinations as CVs (here, methods exist to find optimal combinations; see below).

To identify good candidate measurements for a controlled variable, c, we may use the following four requirements (Skogestad, 2000):

**Requirement 1.** Its optimal value is insensitive to disturbances (so that the optimal variation |Δc|opt is small).
**Requirement 2.** It is easy to measure and control accurately (so that the implementation error |ec| is small).
**Requirement 3.** Its value is sensitive to changes in the manipulated variable, u; that is, the gain, G, from u to c is large (so that even a large error in controlled variable, c, results in only a small error in u. Equivalently, the optimum should be ‘flat’ with respect to the variable, c.
**Requirement 4.** For cases with two or more controlled variables, the selected variables should not be closely correlated.

All four requirements should be satisfied. For example, for a marathon runner, the heart rate may be a good “self-optimizing” controlled variable (to keep at constant setpoint). Let us check this against the four requirements. The optimal heart rate is weakly dependent on the disturbances (requirement 1) and the heart rate is easy to measure (requirement 2). The heart rate is relatively sensitive to changes in power input (requirement 3). Requirement 4 does not apply since this is a problem with only one unconstrained input (the power).

In addition to the above requirements, some systematic approaches to evaluate and find good “self-optimizing” CVs (especially associated with the unconstrained degrees of freedom) are:

**Approach 1 (Brute force).** Conceptually, the simplest approach for finding candidate CVs is the “brute force” approach where one considers the economic loss imposed by keeping a candidate set of CVs constant when disturbances occur (rather than re-optimizing their values),

\[
\text{Loss} = J(CV = \text{constant}, d) - J_{\text{opt}}(d)
\]

The term “brute force” is used because one must do a separate evaluation of each candidate set of CVs. The “brute force” approach is the most general and exact method, but also the most time-consuming method because there are essentially an infinite number of possible CVs (at least if measurement combinations are included) that can be suggested, and for each of them we need to do computations to find the cost for each disturbance.

The “brute force” approach was essentially what we initially tried with strategies I and II for the extraction process, where we evaluated the change in product composition (|Δx_2/Δx_1|) resulting from a disturbance in feed composition.

**Approach 2 (Use analytic expressions or insight about the optimum).** This is not a general approach, but it may be very effective for cases where it works. One useful method is to start from the fact that at the optimum the gradient of the cost J with respect to the degrees of freedom should be zero:

At optimum: \[ \text{Gradient} = \frac{dJ}{du} = 0 \]

These are also known as the necessary condition of the optimum (NCO) (Srinivasan, Bonvin, & Visser, 2003). It seems obvious that the gradient CV = J_c is the “ideal” self-optimizing variable (Halvorsen & Skogestad, 1997; Halvorsen, Skogestad, Morud, & Alsstad, 2003). However, it may be difficult to obtain the expression for J_c or it may depend on non-measured variables.

**Approach 3 (Optimal measurement combinations and nullspace method).** For measurement combinations, the nullspace theorem (Alstad & Skogestad, 2007) can be used to find optimal measurement combinations in a simple manner. This is an improvement of approach 2 for the linear case, where effectively unmeasured variables are eliminated from the expression for J_c. To use the nullspace theorem, we first need to identify the measured variables that we want to combine and these are collected in the vector y. The number of y’s (n_y) must be equal to (or greater than) the number of independent variable at steady-state (n_y) plus the number of disturbances (n_d) that we want to be optimal with respect to, that is, n_y ≥ n_y + n_d. Next, we need to obtain the optimal sensitivity matrix

\[ F = \frac{dy}{dd} \]

Each column in F expresses the optimal change in the y’s when the independent variable (u) is adjusted so that the system remains optimal with respect to the disturbance d. If we have a model of the process, then it is in principle straightforward to obtain F numerically. The nullspace theorem now says that the optimal controlled variable is given by the measurement combination

\[ c = Hy \]

where the matrix H satisfies

\[ HF = 0. \]

Thus the optimal combination H is in the left nullspace of F, which is the reason for calling it the nullspace method. Any number of disturbances (d) may in theory be included, but we since we need n_y ≥ n_y + n_d, we must then include more measurements in y. This requirement is not needed if we use the more general “exact local method” (Alstad, Skogestad, & Hori, 2009; Halvorsen et al., 2003) which can also include the effect of measurement noise, which is neglected in the simpler nullspace method. An analytical expression for H for the “exact local method” is given by Alstad et al. (2009).

**Example 4 (Nullspace method for extraction process; continuation of Examples 2 and 3).** Previously, in Example 3, we found from process insight that c = (F - R)/S is a “self-optimizing” variable with respect to disturbances in feed composition (d_1 = x_F) and
solvent feedrate \((d_2 = S)\); see control strategy \(V\). We now want to
derive this using the systematic nullspace method. For this
particular example, the nullspace method may seem more com-
licated, but in general it is not.

For the extraction process, there is one independent variable at
steady-state \((n_y = 1)\), so we want to find a single \(c = \mathbf{H}y\).
We consider two disturbances \((d_2 = 2)\) so from the condition
\(n_y + n_x = 1 + 2 = 3\), we need to combine at least three mea-
surements. We choose to use three flows (which are all measured),
\[
y = \begin{pmatrix} F \\ R \\ S \end{pmatrix}
\]

The controlled variable combination we are looking for is then
\[
c = \mathbf{H}y = h_1y_1 + h_2y_2 + h_3y_3 = h_1\Delta F + h_2\Delta R + h_3\Delta S
\]
where we have introduced the symbol \(A\) to show clearly that the
nullspace method gives linear measurement combinations in terms
of deviation variables. For the extraction example, optimality is de-
efined as keeping the product composition \(x_0\) constant. Using the
model, the sensitivity matrix \(\mathbf{F}\) becomes
\[
\mathbf{F} = \begin{pmatrix}
\begin{pmatrix} \frac{dF}{ds} \end{pmatrix}_{x_0} & \begin{pmatrix} \frac{dF}{ds} \end{pmatrix}_{y_1} & \begin{pmatrix} \frac{dF}{ds} \end{pmatrix}_{y_2} & \begin{pmatrix} \frac{dF}{ds} \end{pmatrix}_{y_3} \\
\begin{pmatrix} \frac{dR}{ds} \end{pmatrix}_{x_0} & \begin{pmatrix} \frac{dR}{ds} \end{pmatrix}_{y_1} & \begin{pmatrix} \frac{dR}{ds} \end{pmatrix}_{y_2} & \begin{pmatrix} \frac{dR}{ds} \end{pmatrix}_{y_3} \\
\begin{pmatrix} \frac{dS}{ds} \end{pmatrix}_{x_0} & \begin{pmatrix} \frac{dS}{ds} \end{pmatrix}_{y_1} & \begin{pmatrix} \frac{dS}{ds} \end{pmatrix}_{y_2} & \begin{pmatrix} \frac{dS}{ds} \end{pmatrix}_{y_3}
\end{pmatrix}
\end{pmatrix}
\]
\[
= \begin{pmatrix}
\begin{pmatrix} k \\ k \end{pmatrix} F^\prime / S' & \begin{pmatrix} k \\ k \end{pmatrix} R^\prime / S' & \begin{pmatrix} 0 \\ 0 \end{pmatrix}
\end{pmatrix}
\]

The first column in \(\mathbf{F}\) says that the feed flow \(F\) and the raffinate
flow \(R\) have the same optimal sensitivity \(k\) with respect to the dis-
turbance in \(x_0\), whereas the sensitivity in the solvent feed \(S\) is zero
because it is a disturbance. It is only the ratio between the column
elements in \(\mathbf{F}\) that matters, so the numerical value of the constant
\(k\) is not important. The second column in \(\mathbf{F}\) expresses that for dis-
turbances in \(S\) the product composition is kept constant if \(F/S\) and \(R/S\)
are constant. The numerical values follow since at the nominal
point (denoted \(*\)), we have \(F = 100, S = 100\) and \(R = 60\). From
the nullspace method, the optimal combination matrix \(\mathbf{H}\) satisfies
\(\mathbf{HF} = 0\), and we find
\[
\mathbf{HF} = (h_1h_2h_3)
\]
\[
= \begin{pmatrix}
\begin{pmatrix} k \\
0 \\ 0
\end{pmatrix} F^\prime / S' & \begin{pmatrix} k \\
0 \\ 0
\end{pmatrix} R^\prime / S' & \begin{pmatrix} 0 \\ 0 \\ 0
\end{pmatrix}
\end{pmatrix}
\]

We may always select one element in \(\mathbf{H}\) freely, so setting \(h_1 = 1\)
we obtain from the first equation
\(h_2 = -h_1 = -1\)
and from the second equation
\(h_3 = -h_1F^\prime / S' - h_2R^\prime / S' = -(F^\prime / R^\prime)S' = -0.4\).

Thus, the optimal measurement combination is
\[
c = \mathbf{H}y = h_1\Delta F + h_2\Delta R + h_3\Delta S = \Delta F - \Delta R - \frac{F^\prime - R^\prime}{S'} \Delta S
\]
\[
= \Delta F - \Delta R - 0.4\Delta S
\]

As expected, the nullspace method yields a linearized version of
the truly optimal nonlinear variable combination, which we found
from physical arguments is \(c = (F - R)/S\).

**Approach 4 (Maximum gain rule).** The maximum gain rule (Hal-
vorsen et al., 2003) says that one should control “sensitive”
variables with a large scaled gain \(|G|/\text{span}(\text{CV})\). This captures two
main concerns:

1. The optimal value of the \(\text{CV}\) should be approximately constant
   (independent of disturbances), that is, \(\text{span}(\text{CV})\) should be small.

2. The \(\text{CV}\) should be sensitive to changes in the unconstrained degrees
   of freedom (to ensure a flat optimum), that is the gain \(G = \Delta \text{CV}/\Delta \text{MV}\) should be large.

The maximum gain rule can be derived from the exact local
method (with noise) by making some assumptions, which are gen-
erally satisfied except for some ill-conditioned cases (Halvorsen
et al., 2003). An important advantage of the maximum gain rule
is the insight that one should control variables that are sensitive
with respect to the inputs.

### 5. Optimal operation of parallel units

Let us consider an important problem, often encountered in
industrial practice. During the life of production of a product, a
company often expands capacity as demand grows. Early plant de-
sign may involve process designs based on incomplete data as time
to market drives commercialization timelines. Once operation be-
gins, improvements and changes are made in operating conditions,
equipment designs and process topology. When capacity expan-
sion takes places the new capacity may come simply by adding
equipment to the existing process or by construction of a parallel
plant. The new plant is seldom run in a “stand alone” fashion,
but instead may share some unit operations with the existing facili-
ty. As expansion continues, the complexity of the topology among
the plants can lead to plantwide control problems.

In its simplest form, consider a number of plants operating in
parallel, each of differing ages, and each with its own efficiency
and yield relationships that are dependent on throughput. How
should we optimally load each plant to achieve a target production
while minimizing the total production cost \(J\)? We can derive useful
result from the necessary optimality condition \(J_u = 0\). We derive
that, provided the total production rate is given, it is optimal to
load the units such that we have equal marginal costs in all units
(which corresponds to \(J_u = 0\)). This is a well-known fact but a sim-
ple proof is nevertheless enlightening.

**Proof.** To derive this result, consider \(n\) independent parallel units
with a given total load (e.g., given total feed). Let the total cost be
\(J = \sum_i J_i\) and let the total feed (or some other limited load for the
units) be fixed, \(F = \Sigma F_i\). The necessary conditions of optimality is
that \(J_u = \delta J/\delta u = 0\) where \(u\) in this case is the vector of feed rates \(F_i\).
Since the total feed is fixed, there are \(n - 1\) independent degrees of
freedom \(F_i\), and we assume these are the \(F_i\)’s for \(n - 1\) first units
(and for unit \(n\) we have \(F_n = F - \sum_{i=1}^{n-1} F_i\)). The units are assumed to
be independent which means that the cost in unit \(i, J_i\) depends only
on the flow into unit \(i, F_i\). However, note that when we make a change
in \(F_i\) we also need to change \(F_n\), and we have \(dF_n = -dF_i\). The
optimality condition \(\delta J/\delta F_i = 0\) for variable \(F_i\) then becomes
\[
\delta J/\delta F_i = \delta (J_1 + J_2 + \cdots + J_n)/\delta F_i = \delta (J_1 + J_n)/\delta F_i
\]
\[
= \delta J/\delta F_n - \delta J/\delta F_n = 0
\]
or \(\delta J/\delta F_i = \delta J/\delta F_n\). Since this must hold for all \(i\) units, we have
proved that one should operate such that the marginal cost \(\delta J/\delta F_i\)
is the same in same units. \(\square\)

There has been many applications of this criterion. Urbaniczky
and Wattenberger (1994) applied it to the maximization of oil
production of wells that produce both oil and gas, but where
the total gas handling capacity is limited. In their application
\(J_i\) is the oil production and \(F_i\) is the gas production in well \(i\),
and the idea is to operate the wells such that \(\delta J/\delta F_i\) is the same
for all wells; that is, by increasing the gas production by a given
amount \(dF_i\) one gets the same benefit in terms of extra oil produc-
tion \(dJ_i\) in all wells.
Good self-optimizing variables are then the difference in marginal cost between the units (which should be zero). Below we discuss two industrial applications from Eastman.

**Example 5 (Operation of parallel refining systems).** Eastman received an energy efficiency award for 2002 from the American Chemistry Council for its application of advanced control to optimally load three parallel refining systems. Each system consists of four distillation columns used to refine crude reactor product. The application uses process data to establish operating costs for processing material from crude reactor effluent to saleable product. The allocation of load to each system is determined by adjusting the feed rates to each train to achieve equal marginal refining costs.

**Example 6 (Syngas production in parallel furnaces).** For many years Eastman produced synthesis gas by reacting methane and steam in reforming furnaces. The process consisted of 15 furnaces operated in parallel, see Fig. 9. The effluent gas from the furnaces was combined as feed to three carbon dioxide removal systems. The product syngas from the three carbon dioxide removal systems was combined to form a single product gas used in downstream chemical production. The 15 reforming furnaces, constructed over the span of three decades, each had different energy efficiency characteristics as well as different yield performance as technology advanced. In addition, the three carbon dioxide removal systems were of varying efficiency and performance. Newer systems were better instrumented, had valves that performed better, and had on-line analytical measurements. At any time, there were one to three furnaces down for routine maintenance.

The optimum operation of the plantwide system to coordinate pressure and production among the interconnected gas flow network was a significant challenge. The simple objective of matching production of syngas with consumption often ended up varying the production rate on the newest furnace because it could most gracefully handle the needed changes. From an optimization point of view this approach usually resulted in the most efficient units not being operated at their maximum rates.

Often with units in parallel, a reasonable “self-optimizing” strategy is to operate with the same outlet conditions (temperatures or compositions) of all parallel units. At least this avoids mixing losses, and indeed this would have been a good strategy if the reactors were identical. However, in general, and certainly for this example it is more economical to operate each furnace differently based on its particular efficiency and yield profile and then ensure that the combination stream met the total stream specifications. In particular, the newer more efficient furnaces were able to produce a much purer product for the same cost as the older units producing a much less pure product. The purity of the product from each furnace was a relatively weak function of feed rate. The final layer of complexity arises from the efficiency of the carbon dioxide removal system. Each system was connected to a designated set of furnaces so that it was beneficial to operate furnaces linked to the better performing carbon dioxide removal system.

The optimization layer to coordinate the total process production and the allocation of that production to various parallel units was complicated by the presence of crossover lines. These lines added operational flexibility but created an ever increasing complexity of the optimization problem. Local MPC controllers for furnace operation and supervisory control for the carbon dioxide removal systems allowed for near optimal operation at the local level illustrated in Fig. 10. Overall optimization was approached by production loading strategies and coordination using a supervisory MPC controller. As solutions to this problem were developed, it became clear that technology to guide us on the appropriate degree of decentralization was sparse. Developing a centralized system with all the CV’s and MV’s in the same MPC was problematic due to the routine on-line/off-line operation of the furnaces. Being able to gracefully add and remove systems from the overall control system was critical to success. In addition, measurement reliability often resulted in some furnaces being operated in “local” mode; i.e., not connected to the centralized MPC. The eventual control system needed to be developed and commissioned in reasonable time, needed to be implemented on available hardware, needed to be understood by plant operating staff, and had to be maintainable as process improvements were made. This led to a decentralized strategy choice as shown in Fig. 11.

These examples illustrate the complex nature of an industrial plantwide control problem. The use of a formalized procedure can make known improved strategies that may go undetected.

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**Fig. 9.** Syngas process with 15 furnaces and three CO₂ removal systems.

**Fig. 10.** Individual syngas furnace control with three manipulated variables and three controlled variables.
when using only one or two design criteria for guidance. The ability to weave in practical issues that complicate implementation is paramount. Using a formalized procedure can help unscramble the vast array of decisions that can overwhelm designers and cause them to continue reliance upon a unit operation focus.

6. Discussion

The design of plantwide control strategies can be seen from two viewpoints. These are (1) the design of control strategies for the regulation, including that of plant material and energy inventories, and (2) the design of control strategies for process economic optimization. The design of inventory control strategies determines the manipulated variables that remain for process economic optimization. Concepts are needed that guide the design of the inventory control strategy such that the design of the process economic optimization strategy is made easy. It is clear that if a good job is done during the design of the inventory control strategy, such as setting the TPM near the bottleneck, then the remaining process economic optimization strategy design is made easier. On the other hand, if the inventory control strategy results in key optimization variables being far away from available manipulated variables, then strategies for optimizing process economics will be difficult if not impossible to implement.

The emphasis upon placement of the TPM for a process has long been recognized as a key decision in the resulting inventory control strategy. It is becoming more evident that this decision also determines the difficulty of the remaining process economic optimization strategy design. Techniques to determine self-optimizing control variables can be effectively and easily employed if the variables available to optimize the process have good dynamic linkage with their manipulated variable counterparts.

The examples also illustrate that the application of optimization from a top down viewpoint may guide one to select manipulated variables that should remain free for economic optimization while other should be used for inventory control. The formalization of a procedure to organize the design of these two phases of control includes the concepts of: (1) TPM location within the process, (2) control of unit operation process variables against their local constraints, and (3) the development of measurement combinations whose control implies nearness to the economic optimum.

The application of plantwide control design procedures for new plants is certainly an obvious direction of growth. However, the redesign of plantwide control structures for existing plants has been shown to be very beneficial. The known locations of process bottlenecks, known market conditions and product demands, and the operating nuances of a running process all make the plantwide design procedure more understandable and manageable. Using a procedure to determine alternate control structures can lead to new ideas for control that may have been missed for existing processes. As noted, the migration from tried and true control, but inferior, control strategies to new and unfamiliar strategies can be difficult.

7. Conclusion

Since the concept of process control design based on a holistic view of the process came about, the variety of procedures and approaches to the design problem have illustrated the difficulty of a “one size fits all approach”. The examples presented illustrate the application of a few industrial design approaches. A more formal design procedure is presented and it was shown on industrial examples to yield in a systematic way the same control strategies that were obtained with other more ad-hoc criteria. The importance of addressing process economics in the control design procedure is discussed and the industrial need to run plant at their maximum feed rate (mode II) is emphasized. The use of a plantwide design procedure that incorporates and organizes the variety of concerns and technical issues in this important area is demonstrated.

References


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