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Process Control and Energy Efficiency

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Abstract

We review the impact of control systems and strategies on the energy efficiency of chemical processes. We show that, in many ways, good control performance is a necessary but not sufficient condition for energy efficiency. The direct effect of process control on energy efficiency is manyfold: Reducing output variability allows for operating chemical plants closer to their limits, where the energy/economic optima typically lie. Further, good control enables novel, transient operating strategies, such as conversion smoothing and demand response. Indirectly, control systems are key to the implementation and operation of more energy-efficient plant designs, as dictated by the process integration and intensification paradigms. These conclusions are supported with references to numerous examples from the literature.

1. INTRODUCTION

The chemical industry turns raw materials into valuable products via chemical and/or physical transformations. Profitability is paramount (1) and has spurred, on the one hand, the development of ever-larger facilities (the economy of scale) and, on the other hand, the transition from the manual operation and limited product slates of the 1960s to the heavily automated, highly flexible operations of today. The latter represents the automation revolution, of which smart manufacturing (2), a broad designation incorporating a variety of (generally computer-aided) manufacturing technologies, is the latest embodiment. Chemical plant managers must be first and foremost safety minded, with plant economic performance being the next prominent concern. Energy efficiency is key to the latter for several reasons:

- Energy often represents a significant portion of operating cost (typically second only to the cost of raw materials).
- Capital investment decisions concerning facility location and equipment design may hinge on projected energy costs.
- Evolving environmental regulations penalize carbon dioxide emissions associated with fossil fuel use for energy generation.
- As renewables (i.e., solar, wind, hydroelectric) make up an increasingly large percentage of the generation mix on the power grid, electricity-intensive processes must be able to adapt to increased supply (and price) variability associated with these generation sources, while also taking advantage of cost-savings opportunities, such as demand response (DR) programs and even using electricity for process heating.

Improvements in energy efficiency may be achieved via (capital-intensive) design changes—which often materialize in retrofits—that reduce energy intensity by improving equipment performance (e.g., improved heat transfer for enhanced heat recovery). Alternatively, the operation of a process can be modified to maximize production of valuable products at the designed operating point with existing hardware, by, e.g., minimizing variability and wasted energy owing to off-spec product. Responsibility for the latter falls mainly on the process control system.

At the fundamental level, process control systems are largely agnostic to process economics and energy consumption or efficiency. However, as the primary interface with the physical process, the performance of the control system is critical to the successful implementation of economics- and energy-driven changes in both process design and business decisions, such as production scheduling. Consequently, the effect of process control systems on plant economics (and energy efficiency) is both challenging to quantify and important to understand. Furthermore, recent decades have seen the development and widespread adoption of an array of advanced control solutions, notably model predictive control (MPC), whose effect on plant (energy) performance metrics is worthy of discussion. Edgar (1) provided a thorough review of the evolution of process control technology, with an emphasis on its impact on plant economics. The objective of the present article is to discuss the impact of these technologies on process energy efficiency and to delineate commonalities and differences between plant economics and energy efficiency.

2. BRIEF OVERVIEW OF PROCESS CONTROL

The primary functions of chemical process control systems are to (*a*) ensure stable operation at all desired operating conditions, (*b*) drive the process to its desired state (setpoint tracking), and (*c*) return the process to this state when disturbances occur (disturbance rejection) (3). These objectives are typically accomplished using feedback control, in which the process inputs/manipulated

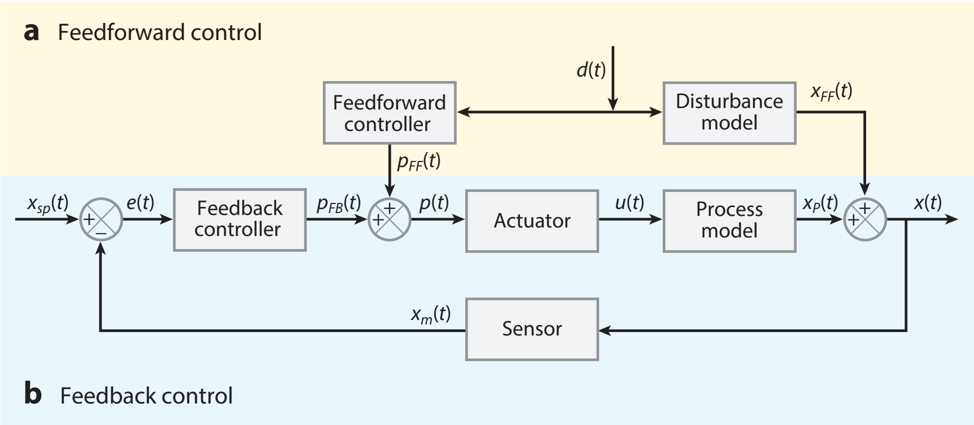

Figure 1

Schematic of a single-input single-output feedback control loop (*b*), with a feedforward controller to mitigate output disturbances (*a*).

variables (MVs), $u(t)$, are varied to drive the process states/controlled variables (CVs), $x(t)$, to their desired values; feedback consists of using updated information from the process, the measured values of the CVs, $x_m(t)$, to compute the values of the MVs. For simplicity, in this work we assume state feedback, i.e., that the process states $x(t)$ are measured and controlled. In practice, measurement is typically restricted to a set of process outputs, which are a function (or a subset) of the process states, $y(t) = g[x(t)]$. A single-input single-output feedback control loop is depicted in **Figure 1*b***.

Feedforward control, depicted in **Figure 1*a***, may be employed to mitigate measurable process disturbances, $d(t)$, e.g., changes in ambient temperature or condition of upstream units/utilities. In the feedforward–feedback paradigm, the signal to the actuator consists of the sum of the outputs of the feedback and feedforward controllers.

Single-input single-output loops that interface directly with the process physical actuators are often referred to as regulatory control. By contrast, advanced process control consists of multi-loop/multivariable configurations (including MPC, discussed later); regulatory controllers are typically the foundation of any advanced control strategy.

2.1. Proportional-Integral-Derivative Control

Widespread industrial application of automatic feedback control first became possible in the 1930s and relied on pneumatic actuation (electronic signaling followed in the 1950s). Early feedback controllers were based on the PID (proportional-integral-derivative) control law (3):

$$p(t) = \bar{p} + K_c \left[e(t) + \frac{1}{\tau_I} \int_0^t e(t^*)dt^* + \tau_D \frac{de(t)}{dt} \right], \quad 1.$$

where parameters K_c, τ_I, and τ_D (controller gain, integral time constant, and derivative time constant, respectively) can be chosen to determine the response time, degree of oscillation, and stability of the closed-loop system. PID control remains the predominant regulatory control strategy in modern chemical processes, with hundreds or even thousands of loops present in a typical plant. According to Edgar (1), a minimalist view of the role of process control was initially adopted, meaning that controllers were tuned to provide good performance at a particular setpoint then largely left alone. Further efforts were dedicated to understanding and minimizing control loop interactions (i.e., the influence of the control action in one loop on the other control loops implemented in the process). This led to the use of tools such as the relative gain array (RGA) and singular value decomposition (3), among others, and to the introduction of the concept of self-optimizing control (4). The latter is predicated on identifying variables that, if kept at their setpoints, ensure some degree of optimality at the level of the plant (5).

2.2. Model Predictive Control

The 1973 energy crisis caused the price of oil to more than triple within a year, causing a significant shock to the US manufacturing and energy sectors. Refineries were increasingly operated at their capacity limits, typically represented by equipment throughput or safety constraints. Thus, a major drawback of traditional PID control was exposed: the lack of a mechanism by which to enforce process constraints. In response, control practitioners rapidly adopted solutions that made use of ideas from modern control theory (i.e., optimization-based control using dynamic process models), while circumventing some of the difficulties facing early applications (namely, the challenges of developing and maintaining first-principles models of complex, multivariable processes). Several new algorithms were proposed that fall under the umbrella of what is now known as MPC.

MPC consists of solving, at each sample time, an online optimization problem for the optimal sequence of control moves, subject to a (typically linear) dynamic model of the process and a set of process constraints:

$$\begin{aligned} \min_{\mathbf{u}} \quad & \sum_{k=1}^{N-1} ||x_{sp}(k) - x(k)||_Q^2 + ||u(k)||_R^2 & \\ \text{s.t.} \quad & x(k+1) = f_{MPC}(x(k), u(k)) & k \in \mathbb{I}_{0:N-1}\ , \\ & (x(k), u(k)) \in \mathbb{Z} & k \in \mathbb{I}_{0:N-1} \end{aligned} \qquad 2.$$

where $f_{MPC} : \mathbb{X} \times \mathbb{U} \to \mathbb{X}$ is a model of the process dynamics (usually linear and obtained empirically from tests/experiments carried out in the plant); the sets $\mathbb{X}$ and $\mathbb{U}$ denote the constraints on the CVs and MVs, respectively; $\mathbb{Z} \subseteq \mathbb{X} \times \mathbb{U}$; and the set $\mathbb{I}_{0:N-1}$ denotes the set of integers $\{0, 1, \ldots, N-1\}$. The quadratic objective function, borrowed from linear quadratic Gaussian (LQG) theory, penalizes deviations from setpoint and the control effort according to the values of the elements of the weighting matrices Q and R, respectively. Proper MPC tuning ensures the process is driven quickly to its setpoint after a setpoint change or disturbance, while avoiding excessive oscillation and respecting stability limits. The optimization problem in Equation 2 is solved over a finite time horizon, N. A moving time window is used: At a sample time k, the first optimal control move, $u(k)$, is implemented; the optimization problem is then resolved at time $k+1$, taking into account feedback in the form of the measured values of CVs.

MPC represents a significant improvement relative to traditional multi-loop PID control owing to (*a*) inherent handling of process constraints within the optimization framework and (*b*) the ability to account for complex, multivariable interactions when determining the control action, particularly in the context of nonsquare systems (having a different number of inputs and outputs). PID controllers do not have direct means to enforce bounds on CVs and cannot explicitly account for interactions between multiple input and output variables; at best, interactions are dealt with by finding loop pairings that minimize them using, e.g., the aforementioned RGA.

Model predictive controllers became commercially viable in the 1980s as the cost of computing hardware dropped, and their adoption continues to expand. Qin & Badgwell (6) reported that, as of 1999, there were at least 4,500 MPC applications worldwide; this number is likely much higher today. Numerous extensions of MPC have been proposed, designed to account for process economics [economic MPC (7)], process nonlinearities [nonlinear MPC (8)], and uncertainty [stochastic MPC (9), robust MPC (10)].

2.3. Real-Time Optimization

Practitioners recognized early on that extracting the maximum economic value from MPC required real-time optimization (RTO) of the controller setpoints (11, 12). RTO consists of maximizing an economic objective by selecting the MPC targets/setpoints:

$$\begin{aligned} \min_{u_{sp},x_{sp}} \quad & V(u_{sp}, x_{sp}) \\ \text{s.t.} \quad & 0 = f_{RTO}(u_{sp}, x_{sp}), \\ & (x_{sp}, u_{sp}) \in \mathbb{Z} \end{aligned} \qquad 3.$$

where the decision variables u_{sp} and x_{sp} are the setpoints provided to the MPC. In contrast to MPC, which uses a dynamic, but typically linear, model, the model f_{RTO} used in RTO is generally nonlinear and steady-state. Under the two-tiered RTO–MPC structure, real-time economically relevant data (e.g., price and/or quality of feedstock and utilities) and plant-wide economic objectives inform the setpoints toward which the MPC must drive the process. The combination of RTO and linear MPC is currently the de facto industry standard for advanced control of multivariable systems; however, significant gaps between the academic literature and the industrial applications have been noted (13) and continue to persist. A relevant example is the relatively recent development of RTO using dynamic models (14).

2.4. Quality Control

Along with the development of MPC, the 1980s and 1990s saw a renewed interest in quality control, building on statistical process control concepts first introduced in the 1920s (1). Reducing variability in process operations became an important goal toward increasing competitiveness: Latour et al. (15) demonstrated that variability could be controlled dynamically using advanced control and measurement systems and emphasized the link between reducing variability and maximizing equipment utilization (e.g., mitigating high variability in product quality may be dealt with by blending, which leads to product/energy waste). Reduction in output variance thus emerged as a control performance metric (16).

2.5. Enterprise-Wide Optimization

As hardware and algorithmic capabilities have continued to improve since the 1990s, the role of mathematical optimization in plant operations has increased considerably. **Figure 2** depicts the decision-making hierarchy of a chemical manufacturing enterprise, spanning multiple time and spatial scales. The decisional layers have typically been implemented by separate entities/business units within the enterprise—often with relatively little communication or information feedback—likely leading to suboptimal (overall) process operations. For example, if equipment is designed for a steady-state operating point where control (e.g., in the sense of disturbance rejection) is difficult, much of the investment in that design will be unwarranted. In response to this realization, enterprise-wide optimization, which seeks to optimize chemical process operations across all levels of the hierarchy in **Figure 2**, has been the subject of a significant body of research in recent years (17). The implications of the enterprise-wide optimization philosophy for the control layer might include, e.g., consideration of controllability and design of the control system at the unit design stage, as well as the integration of planning/scheduling/control layers.

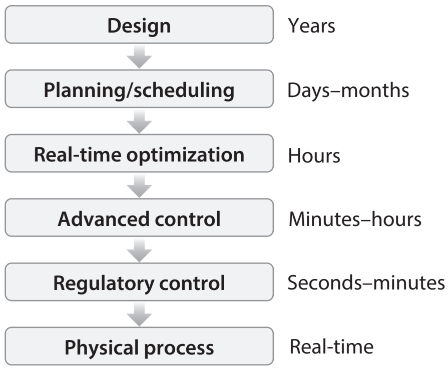

Figure 2

Hierarchy of decision making in the chemical process industries.

3. ENERGY EFFICIENCY OF CHEMICAL PROCESSES

Economic considerations notwithstanding, energy efficiency has become a matter of public and policy interest owing to growing concerns regarding the finite supply of carbon-based fuel sources and the role of CO_2 emissions in climate change. Nevertheless, in the United States and around the world, efforts to reduce aggregate energy consumption across the economy have largely been eschewed in favor of technological solutions that make processes and products more (energy) efficient (18). At a high level, energy efficiency typically refers to using less energy to produce the same quantity of goods or useful outputs (19):

$$\mathrm{EE} = \frac{\text{useful output of a process}}{\text{energy input to a process}}. \tag{4}$$

More specific definitions of energy efficiency have been proposed, e.g., based on the first law of thermodynamics:

$$\mathrm{EE}_{\Delta H} = \frac{\Delta H_{out}}{\Delta H_{in}}, \tag{5}$$

where ΔH_{out} and ΔH_{in} are the enthalpies of the process outputs and inputs, respectively. However, the definition in Equation 5 does not consider the quality of the energy inputs and outputs, and processes with different energy inputs cannot be meaningfully compared using this metric. Thus, for the purpose of comparing two processes (e.g., at the design stage), it is generally more useful to consider metrics based on the second law of thermodynamics, such as exergy efficiency (19).

A more practical definition is based on the amount of energy required to produce a certain quantity of final goods:

$$\mathrm{EE}_{\mathrm{econ}} = \frac{\text{quantity of valuable product}}{\Delta H_{in}}. \tag{6}$$

Discussions on energy efficiency often implicitly emphasize a reduction in energy consumption from carbon-based fuel sources. The inclusion of renewable energy sources (e.g., solar, wind) is viewed as socially and environmentally positive because such renewables reduce CO_2 emissions, even though their use is not necessarily more thermodynamically efficient, according to Equation 5.

3.1. Energy Intensity of Chemical Processes

A (unit of a) chemical plant can be modeled as an open thermodynamic system that transfers energy and mass across its boundaries. The energy sources and sinks within these units may be endogenous, e.g., related to enthalpy of reaction or enthalpy of solution, or exogenous, carried by utilities or in the form environmental losses. The energy intensity of a process, a closely related concept to energy efficiency (Equation 4), can be defined as the amount of energy required to perform a specified operation at a given throughput. Chemical processes can be broadly categorized based on the nature of their energy-intensive characteristics:

- High utilization of hydrocarbon fuel (e.g., distillation, catalytic cracking)
- High electricity use (e.g., ammonia, electrolysis)
- High-temperature operation (e.g., glass, metal processing)
- Low-temperature operation (e.g., cryogenic air separation, natural gas liquefaction)

There are numerous other reasons for high energy intensity, and combinations thereof must be taken into account when considering the entire (chemical) supply chain (e.g., energy consumption associated with transportation of raw materials). Energy intensity and total energy use also vary considerably across industries. Refining, for example, involves processing significant volumes of crude material (the largest refineries in the United States process hundreds of thousands of barrels per day), using primarily hydrocarbon fuels to drive separation and high-temperature reaction of components. In such cases, the economy of scale can be leveraged to improve energy use performance: Even a small (e.g., 1%) relative decrease in energy consumption is significant in absolute terms.

3.2. Process Control, Energy Efficiency, and Plant Economics

Continued investment in modern control systems can ultimately be attributed to the belief among control engineers and plant managers that improved control increases profitability (**Figure 3**). Although reducing cost often involves reducing energy consumption (per unit product), improving energy efficiency is rarely a goal in its own right. Furthermore, the macroeconomic impacts of improvements in energy efficiency are uncertain. When reduced energy costs decrease the price of final products, user demand may increase, resulting in higher total production and possibly higher net energy use. This phenomenon, known as the rebound effect (20), may negate relative improvements in energy efficiency in a free market system. There are even scenarios in which economics and energy efficiency appear completely at odds. For example, demand response (DR) (discussed later in this article) operation of electricity-intensive manufacturing processes entails increasing production at off-peak hours (when electricity is cheap) and storing excess product, which is then used to fulfill demand during peak hours when electricity is more expensive. Although DR may improve process economics, it generally requires a net increase in energy consumption, owing to increased storage demands (e.g., in the case of cryogenic air separation, storage entails energy-intensive liquefaction of products). Proponents argue, however, that DR enables a more extended adoption of carbon-neutral (and time-varying) electricity sources, such as wind and solar, by providing load-shifting services to the grid. As such, DR is associated with increased total energy consumption but decreased carbon emissions.

The discussion above emphasizes that the relationship between the control system and realized energy efficiency of a process is complex and multifaceted. Their interaction is fourfold:

1. Direct effects, whereby reducing variation allows operating points to be shifted in the direction of higher energy efficiency.

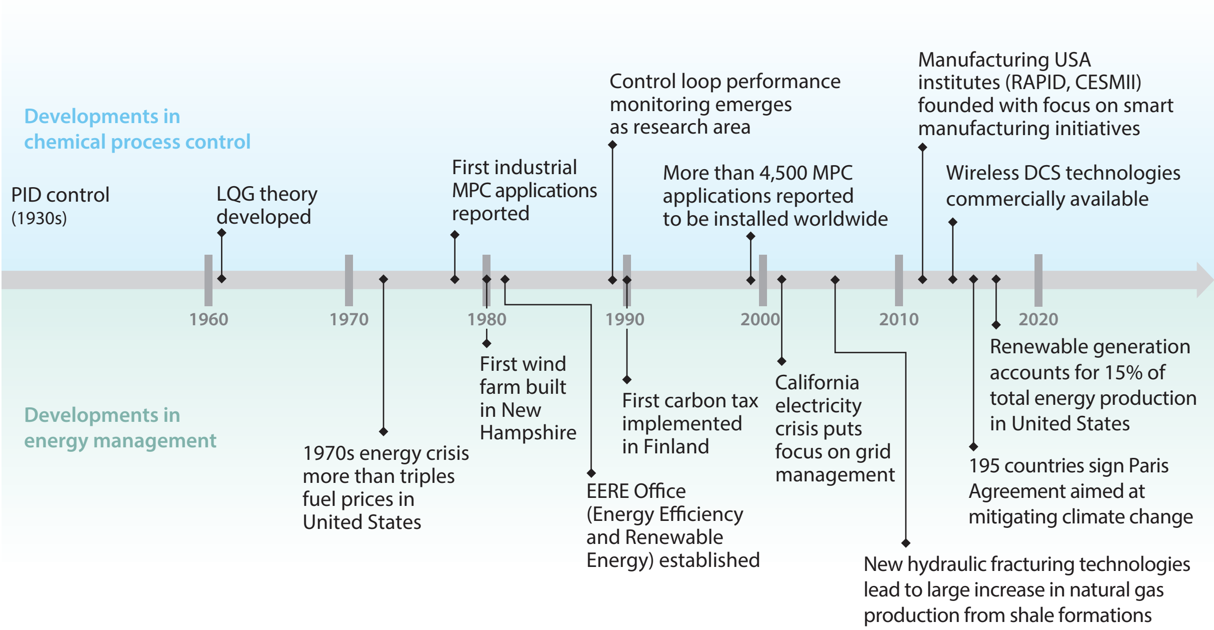

Figure 3

Selected developments in chemical process control (*top*) and energy management (*bottom*) since 1960. Abbreviations: DCS, distributed control system; LQG, linear quadratic Gaussian; MPC, model predictive control; PID, proportional-integral-derivative.

2. Direct effects, whereby energy minimization is an explicit objective of the process control system.
3. Indirect effects, whereby process control enables more energy-efficient operational paradigms.
4. Indirect effects, whereby process control systems facilitate the implementation of more energy-efficient integrated/intensified process designs.

These effects are considered in detail in the next sections.

4. THE DIRECT LINK BETWEEN PROCESS CONTROL AND ENERGY EFFICIENCY

Process (particularly regulatory) control systems are rarely designed to explicitly reduce energy consumption or improve energy efficiency (21). Relatively little attention has thus been given in the literature to the direct relationship between control and energy efficiency: That is, what effect do the design and performance of the control system have on the realized energy efficiency of the process? In industry, however, advanced control has long been recognized by practitioners as one of the most cost-effective means by which to improve process performance (22) and, potentially, to reduce energy consumption. Such cost/energy savings occur when process control reduces output variability and enables operation closer to constraints.

4.1. Reducing Process Variance via Improved Control

From the pragmatic perspective of the plant engineer, a primary benefit of control is the reduction of process output variance. Harris (16) first proposed benchmarking the (closed-loop) output variance achieved by a controller against the value reachable with a theoretical minimum variance controller (the latter estimated using a time series analysis of closed-loop process data):

$$\eta = \frac{\sigma_y^2}{\sigma_{MV}^2}, \tag{7}$$

where σ_y^2 is the variance of the observed outputs under the given control scheme and σ_{MV}^2 is the theoretical minimum variance.

Extensions have been proposed for multivariate systems (23, 24) and to account for trade-offs between input and output variance (i.e., the LQG benchmark) (25, 26). Although minimum variance controllers are rarely implemented in practice [they tend to be overly aggressive, among other limitations (27)], output variance can be reduced to an acceptable level by proper tuning of PID controllers (28); use of advanced control structures, such as feedforward and cascade designs (1); improved sensing capabilities (29); and use of model-based control (30). In fact, reduction in output variance can be understood as a primary motivation for the development of MPC: Because dynamics are accounted for explicitly, the process can transition to a new setpoint or can reject disturbances more effectively compared with a control structure (e.g., multi-loop PID) in which the process dynamics are captured at best indirectly in the form of control loop pairing and controller tuning parameters.

4.2. Energy-Efficiency Benefits of Reduced Process Variance

Economically optimal operating points often lie at (the intersection of) process constraints/bounds, which in many cases are correlated with energy consumption. Historically, operators have tended to operate plants conservatively (i.e., away from such limits) to avoid violating critical constraints. A controller that reduces output variance therefore enables operation closer to constraints without violating them (**Figure 4**).

In one of the earliest works to explicitly link control and energy efficiency, Shinskey (31) identified several conservative operating policies in the petrochemical industry, including (*a*) excessive reflux in distillation operations (to avoid penalties associated with off-spec production), (*b*) overly conservative column pressure targets (to avoid flooding of distillation column trays), and (*c*) excessive combustion air in furnace operation (to avoid violation of emissions constraints and to prevent explosions). These situations exemplify opportunities to save energy by implementing control strategies that reduce variance.

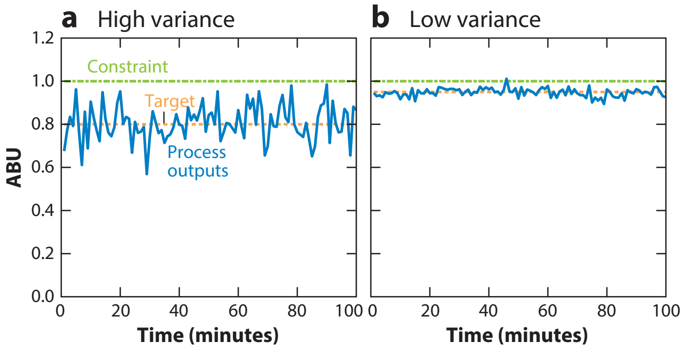

Figure 4

Reducing output variance allows processes to be operated closer to constraints/bounds.

Operating closer to constraints can improve energy efficiency by increasing throughput at a given product quality. Consider a gas-fired heater that is constrained by an upper bound on the tube skin temperature (22). A controller that reduces temperature variance allows the operator to set a higher temperature target (i.e., closer to the maximum tube skin temperature). This, in turn, enables either (*a*) higher throughput of the unit, at a fixed exit temperature, or (*b*) higher exit temperature of material processed in the unit, at a fixed throughput.

In the first case, the energy efficiency of the unit is directly increased by improved control, because less energy is expended per unit of processed material. In the second case, the economic value of products is directly increased by improved control. This latter scenario may still represent an improvement in energy efficiency if, in the absence of improved control, the material would require, e.g., increased recycle or processing in downstream units to meet quality requirements.

White (32) presents another example, pointing out that operating targets need not change in order to improve energy efficiency when process energy use is a nonlinear function of the process variable(s). White illustrates this idea with a distillation column operated at constant bottoms composition, where the reflux rate is varied to control the distillate composition. The total energy consumption rate is an approximately linear function of the reflux rate; distillate composition, however, is a nonlinear function of reflux rate (and thus energy consumption), because further increases to reflux rate yield diminishing returns as the rate tends to infinity. A low-variance distillate composition controller will lead, on average, to lower energy consumption than a controller that results in higher variance, for the same average product quality.

4.3. Energy Savings Under Model-Based Control

Richalet et al. (33) described one of the first MPC applications, IDCOM (for "identification and command"), and described its implementation in a series of distillation columns in a PVC plant. It was claimed that reduced variance of the controlled temperatures and robustness to disturbances under IDCOM allowed operators to reduce constraints on minimum column outflow rate while maintaining product quality. This led to a 15% reduction in steam flow rate, with combined annual energy savings across two columns reported to be \$220,000 (1978 dollars). Another early MPC product, Dynamic Matrix Control (DMC) (34), was demonstrated on a furnace temperature control application, yielding improved performance compared with conventional feedforward strategies. Later, Kano & Ogawa (35) presented the example of an olefins unit at the Mitsubishi Chemical Co. (MCC) Mizushima plant, where a large-scale MPC/RTO application enabled variable column pressure operation. This translated into significant energy savings relative to the constant pressure operation that operators had favored for decades: The authors claimed a 3–5% reduction in energy use across the complex. Working on the same MCC facility, Gao et al. (27) claimed an 18% reduction in energy consumption for a para-xylene unit following MPC implementation.

Energy-intensive plants outside the chemical industry can also benefit from MPC. In the metal processing realm [nearly 6% of US industrial energy consumption (36)], Ganesh et al. (37) proposed the use of MPC in an austenitization furnace operating at high temperatures, where the temperature of the processed parts at exit is controlled as a proxy for mechanical properties that are subject to strict quality specifications. The authors demonstrated that MPC reduced part temperature variability, allowing for the target exit part temperatures to be lowered relative to the (conservative) heuristic target that furnace operators had historically enforced to ensure part quality. Total energy savings were estimated at 5.3%. Worrell et al. (38) discussed the application of advanced control to (high-temperature) cement clinker production [a sector responsible for approximately 1.6% of US industrial energy usage (36)], reporting energy savings between 2.5%

and 10% and payback periods as low as three months. Energy savings from implementing MPC on a glass melting furnace [glass makes up 1.1% of US industrial energy use (36)] were estimated at 2–3%, with payback under six months (39).

There are several considerations to keep in mind when assessing the potential benefits of implementing MPC. First, model-based control systems require accurate process models; these are generally obtained in a series of (typically costly and time-consuming) plant step tests. Second, dedicated maintenance of the underlying models is needed to retain good performance over time. Lastly, as Richalet (40) and Qin & Badgwell (6) pointed out, MPC reduces process variance and enables operation closer to constraints, but appropriate targets/setpoints must be provided (e.g., via RTO) for a meaningful economic/energy-efficiency impact. Despite these caveats, it is reasonable to state that, with thousands of MPC applications worldwide (6), cumulative energy savings owing to model-based control are significant.

4.4. Energy Savings Related to Proportional-Integral-Derivative Control Loops

PID controllers remain the fundamental feedback control mechanism in the process industries; even the output of MPC systems is often a set of setpoints provided to regulatory PID control loops that interface with the physical actuators. Tuning and maintenance of these regulatory loops are thus critical to ensuring good (advanced) control performance, so that process targets can be shifted in the direction of improved energy efficiency. Most modern PID controllers come equipped with auto-tuning (41) and, increasingly, controller performance monitoring capabilities (42). In the 1990s, spurred by the introduction of the minimum variance and related benchmarks, control researchers introduced methods for detecting and diagnosing the root cause of oscillations in single-input single-output control loops (43, 44).

Desborough & Miller (45) presented a survey of the state of industry in control loop management, with an emphasis on business and energy drivers. The authors noted that only a third of control loops exhibited good control performance, according to control practitioners, and provided practical recommendations for implementing plant-wide control loop monitoring. Of note for this review, the authors listed energy savings as a desirable outcome of improved (regulatory) control performance and estimated that implementation of the proposed monitoring tools could reduce plant-wide energy usage by 1% (a "conservative" estimate of $300 million in potential annual energy savings across the US process industries was also provided). More recent literature contributions from industrial practitioners and control hardware/software providers continue to place emphasis on maintenance of PID control loops as a complement to advanced control (28). Bonavita (46) reported a 10% reduction in energy consumption at an advanced materials plant as a result of software-assisted retuning of hundreds of PID control loops. Lang et al. (47) described the diagnosis of poor control performance in a distillation column at a petrochemical plant, tracing the origin of plant-wide oscillations to a regulatory pressure control loop. Importantly, these oscillations were neither caused nor dealt with by the MPC system, emphasizing the importance of regulatory control loops to fully realize the benefits of advanced control.

4.5. Improved Sensing for Energy Efficiency

Control systems are fundamentally limited by the existence, placement, dynamics, and precision of sensors, which measure the physical process variable levels and relay this information to the controller. A full discussion of optimal sensor design and placement is beyond the scope of this review (the reader is referred to, e.g., References 48 and 49). However, it is important to acknowledge the role that improved and innovative sensing plays in enabling a more energy-efficient operation.

Kumar et al. (29) proposed a distributed temperature sensing approach for furnace balancing (i.e., minimizing variability of tube-wall temperatures) in a steam methane reformer with hundreds of tubes and dozens of burners. An array of infrared cameras was used to reconstruct the spatial temperature distribution in the furnace. This information was provided as an input to an optimization problem that determined (based on a reduced-order process model) the appropriate fuel distribution to the furnace. A 44% reduction in tube-wall temperature variability was demonstrated under this framework (with significant implications for energy savings), compared with the case where the temperatures of only a few tubes were periodically but infrequently measured by an operator.

In addition to sensors that directly measure the CV of interest, it is often prudent to use soft sensors, meaning that a (set of) secondary, easier-to-measure variable(s) is used as a proxy for a difficult-to-measure CV (1); control using soft sensors is referred to as inferential control. A canonical example is in distillation, where temperature is used to infer composition to avoid the long time delays associated with direct composition measurement. Although models based on first principles can be used when available (50), soft sensors tend to rely on data-driven (black box) models; these include classical techniques from multivariate statistics (e.g., principal component analysis and partial least squares, which are also common in fault detection) and computational learning methods (artificial neural networks, neuro-fuzzy systems, and support vector machines) (51). Soft sensors often attempt to shift the burden in difficult measurement problems from installation of new sensors (capital intensive, especially in severe process environments, but easy to interpret) to increased modeling efforts (typically reducing implementation cost but requiring sophisticated model development and maintenance).

5. EXPLICIT OPTIMIZATION OF ENERGY CONSUMPTION USING ECONOMIC MODEL PREDICTIVE CONTROL

Economic model predictive control (EMPC) bridges the gap between RTO and supervisory process control by directly optimizing some process performance metric (7, 52). Although it was originally aimed at improving economic performance, EMPC can explicitly consider energy and/or utility consumption, thereby enhancing process energy efficiency. We summarize the key features of EMPC that pertain to improving process energy efficiency; the reader is directed, e.g., to the work of Ellis et al. (53) for a comprehensive review of EMPC.

Similar to conventional MPC (Equation 2), EMPC is cast as an optimization problem solved on a receding horizon. Thus, at each sampling time (we utilize the notation in Reference 7),

$$\begin{array}{lll} \min\limits_{\mathbf{u}} & V_{EMPC}(x, \mathbf{u}) & \\ \text{s.t.} & x(k+1) = f_{EMPC}(x(k), u(k)) & k \in \mathbb{I}_{0:N-1} \\ & (x(k), u(k)) \in \mathbb{Z} & k \in \mathbb{I}_{0:N-1} \\ & x(0) = x_0 & \end{array}, \qquad 8.$$

where $f_{EMPC} : \mathbb{X} \times \mathbb{U} \to \mathbb{X}$. A key departure from conventional MPC (Equation 2) is the objective function:

$$V_{EMPC}(x, \mathbf{u}) = \sum_{k=0}^{N-1} \ell(x(k), u(k)), \qquad 9.$$

where $\ell : \mathbb{X} \times \mathbb{U} \to \mathbb{R}$ represents the stage cost and is a generic cost metric—potentially related to energy efficiency—for the process states and control inputs. The economically optimal steady state x_s is the minimizer of $\ell(\cdot)$ satisfying $x_s = f_{EMPC}(x_s, u_s)$. We note that representations may differ slightly in the literature. The optimal control problem in Equation 8 is typically accompanied by terminal conditions, such as a terminal equality constraint, $x(N) = x_s$; a terminal region constraint, $x(N) \in \mathbb{X}_f$; or a terminal cost penalty, $V_{f,EMPC}(x)$, as an additional term in the objective function.

5.1. Economic Model Predictive Control and Process Energy Efficiency: Impact and Limitations

Several case studies available in the open literature discuss the energy-efficiency benefits of EMPC implementations. Amrit et al. (54) studied the benefit of directly optimizing process economics relative to standard tracking MPC using a simple prototype process consisting only of physical transformations. Gopalakrishnan & Biegler (55) demonstrated improved economic performance, relative to tracking MPC, for periodic operation of gas pipeline networks (which in this case translated directly to compressor energy savings) under nonlinear EMPC. Nonlinear EMPC has also been proposed for control of air separation units (56, 57) and water distribution networks (58). Interestingly, several authors highlighted the tendency of EMPC systems to impose cyclic operating regimes (53, 59) as a means to improve process economics.

As an emerging technology, EMPC is competing with a large base of conventional MPC implementations and well-established and industry-tested MPC software packages. Practitioners also appear to be wary of the associated need to solve (nonlinear) optimization problems (Equation 8) online and in real time. EMPC case studies discussed in the open literature generally deal with low-complexity, low-dimensional processes. By contrast, the application of conventional MPC to large-scale systems with dozens of input and output variables is by now routine. At the theoretical level, EMPC lacks widely applicable theoretical guarantees for closed-loop stability (60). Current developments in stability rely on synthesizing appropriate terminal conditions (applicable at the end of the prediction horizon), an endeavor that involves significant process knowledge and computational effort. It is worth mentioning that this may not be a hurdle per se: Although the stability of conventional MPC systems is by now well understood, this was not the case when the first industrial implementations were reported.

5.2. HVAC Energy Management via Economic Model Predictive Control

Buildings [which consume nearly 40% of the total energy used in the United States (61)] and their HVAC systems are particularly well suited for EMPC implementation for several reasons: (*a*) System dynamics are relatively simple (not involving, e.g., chemical reactions, phase equilibria), slow, and dissipative, and (*b*) it is sufficient to control building temperature to within a range (rather than to a specific setpoint) to ensure the comfort of occupants. Furthermore, electricity prices and relevant disturbances (weather, building occupancy) can be forecasted relatively accurately. Under EMPC, these forecasts are used to shift energy loads to off-peak hours via thermal energy storage, which may be passive (precooling/preheating of building zones) or active (using, e.g., chilled water) (62).

We note that EMPC is not guaranteed to increase energy efficiency of HVAC systems, because it is usually designed to minimize energy cost; thermal losses associated with thermal energy storage also tend to require an increase in total energy consumption. The load-shifting services provided to the grid are nonetheless important for fully leveraging renewable energy sources and reducing dispatch of (hydrocarbon-fueled) peak-load plants. However, maintaining indoor temperatures within a range (rather than tracking a constant setpoint) can directly reduce energy consumption by allowing temperatures to reach the upper/lower bounds during the hottest/coldest hours of the day. Several works have reported economic savings under EMPC in commercial (63–66) and residential (67, 68) buildings.

6. PROCESS SCHEDULING, CONTROL, AND ENERGY EFFICIENCY

In this section, the intersection of scheduling/operations and energy efficiency in the literature is reviewed, focusing on the role of control. Energy-efficient scheduling paradigms work either by reducing overall energy usage or by temporally redistributing energy usage to reduce emissions and/or waste. The resulting schedules tend to be highly dynamic, featuring relatively rapid transitions between operating points. Satisfactory control performance is therefore essential for executing the schedules and realizing the associated energy benefits.

6.1. Reducing Energy Consumption

Scheduling activities can contribute to reducing total energy use in chemical and manufacturing plants by (*a*) improving transitions between operating points and/or products in the product wheel (mainly relevant to continuous processing) and (*b*) energy-optimized plant configuration and resource/task assignment (discrete manufacturing and batch processes).

6.1.1. Continuous processes. In the case of continuous processes, scheduling decisions amount to establishing the timing and sequencing of making the products in a product wheel and inevitably include transitions between the corresponding operating points. Another potential scheduling application entails modulating the production rate of the same product(s) over a continuous range of values based on an exogenous signal (e.g., energy prices). It is generally assumed that the process can transition between the operating states identified at the scheduling level, with the transitions being imposed by the control system. Poor closed-loop performance can render such transitions a cause of energy inefficiency; for example, improperly tuned controllers may have excessive settling times, resulting in wasted product and increased energy use. Process nonlinearity can also make certain transitions more expensive than others. These factors require that production scheduling models consider explicitly the dynamics of the process and the performance of its control system.

Work by Bhatia & Biegler (69) and later by Terrazas-Moreno et al. (70) demonstrated that significant economic benefits arise from accounting for process dynamics at the scheduling stage. Prata et al. (71) extended the grade transition problem to include flowsheet changes that are dependent on the optimal production sequence. Du et al. (72) introduced computationally efficient modeling approaches for representing the scheduling-relevant closed-loop dynamics of a process and its control system. Using a multiproduct continuous stirred tank reactor (CSTR) as an example, Costandy et al. (73) were able to identify both an upper bound on potential economic gains by improved process control and specific areas of a process where improved control performance was needed, using total transition time and transition time between products as metrics. They concluded that the improved economic performance of the process, owing to reducing product waste during transitions, implied that more energetically favorable operating schedules can be generated when process control performance is improved.

6.1.2. Discrete manufacturing. A direct way to reduce energy consumption via optimal scheduling involves turning off idle machines/equipment and using optimal scheduling principles to determine when to bring machines on-/offline. Prabhu et al. (74) characterized energy dynamics as they relate to machine- and production-level control in an exploratory study of energy efficiency in discrete manufacturing systems. A simulation model with bi-level integrated control policies demonstrated that parameters in the production control (scheduling) policies drastically changed the energy performance (as it relates to energy losses) (74). Mouzon et al. (75) developed optimization algorithms for a set of dispatching rules for machine-level controllers, considering the energy (and time) required to start up, idle, use, and shut down manufacturing equipment, and paired these algorithms with an artificial neural network to determine when a product order would arrive. The authors found that energy-efficient scheduling was most effective when equipment bottlenecks were reduced and machines following any remaining bottlenecks were turned off until sufficient input (intermediate product) was ready for processing (75).

6.2. Temporal Redistribution of Energy Usage

From a thermodynamic perspective, large, rapid changes in process energy use can increase energy waste. Conversion smoothing represents an operational strategy that seeks to minimize the rate of change of energy use over time. Rager et al. (76) applied this scheduling philosophy to textile manufacturing systems with parallel machines.

Energy storage is another means for shifting process energy use in time. Numerous works have considered the DR operation of chemical processes as a means of storing energy in the form of product. DR involves overproducing and storing product(s) when electricity demand (and price) is low. When electricity demand (and prices) peaks, the chemical process can operate at a lower production level and use previously stored product to meet customer demand. DR programs are well suited to electricity-intensive chemical processes, such as air separation (77, 78) and chlor-alkali plants (79, 80). The economic incentive for DR operation is provided by the discrepancy between peak and off-peak electricity prices, which can be quite significant in deregulated markets. Furthermore, electricity prices fluctuate hourly (or more frequently) during the day, requiring that the operating state (and electricity demand) of the plant change at a similar pace (81). DR operation therefore calls for a new production scheduling strategy: a transient operation regime is implicitly assumed by selecting scheduling time slots that are significantly shorter than the settling time of the process.

Naturally, the performance of the control system and its ability to impose the frequent transitions prescribed by the scheduling calculations are paramount to the engagement of a chemical plant in DR operation schemes. As a consequence, many applications seek to explicitly include a description of the process dynamics and control in the scheduling model. Using first-principles process models can increase scheduling model size (and solution time) significantly (77). Considerable research efforts have been invested in devising computationally parsimonious representations of process dynamics and control in scheduling calculations. System identification techniques were proposed for building scale-bridging models, i.e., low-order nonlinear surrogate dynamic models of the closed-loop process dynamics. The structure of the model can be selected using either empirical arguments (77) or machine learning techniques (82). Exact linearizations of such representations were discussed by Kelley et al. (83), and extensions to closed-loop scheduling were presented by Pattison et al. (84). In a different vein, Huang et al. (85) developed a model-free industrial DR scheme, which used a Markov decision process and an actor-critic-based reinforcement learning algorithm for optimal energy management of steel powder manufacturing. Zhang et al. (86) used a resource-task network model to perform scheduling of steel plants while also considering their interaction with the power grid.

As pointed out earlier, although DR does not improve the energy efficiency of a plant, DR initiatives are beneficial at the level of the power grid. They enable increased use of renewables and, consequently, can lower greenhouse gas emissions associated with power generation and transmission (87, 88).

7. THE RELATIONSHIP BETWEEN PROCESS DESIGN, CONTROL, AND ENERGY EFFICIENCY

Although the above operational benefits of process control are important considerations, the energy efficiency of a chemical process is ultimately limited by its design and the physical characteristics of the process units. As we argue below, the control of a process may become more difficult with improvements in equipment-level energy efficiency, which usually require tighter heat integration and therefore, e.g., higher dynamic interactions between units and minimal physical driving forces. Advances in process control technology have played an indirect, but crucial, role in improving energy efficiency at the process design stage by enabling the safe and reliable operation of apparently less controllable (but more energy-efficient) process designs.

7.1. Control of Integrated Processes

Energy and material integration in process design can significantly reduce waste products, decrease energy consumption from utilities/external sources, and maximize process throughput. Tight energy (and material) integration seeks to maximize these process efficiency benefits but results in complex, multiple-timescale dynamic behavior, as well as potential losses in control degrees of freedom (89). The latter can be attributed to newly introduced interdependencies (e.g., preheating a stream with a warm process stream in a feed-effluent heat exchanger versus using a steam heater). Safe and reliable operation of these energy-efficient but highly interconnected designs thus typically requires model-based controllers that can properly account for the relevant dynamic interactions, such as MPC, discussed earlier.

Alternatively, decentralized/distributed-model control strategies have been proposed to handle large-scale, interconnected processes. Such strategies have an intuitive motivation, as they divide control systems using knowledge of the interconnected component subprocesses, but coordination of the individual control systems introduces new challenges with respect to stable and optimal operation of the entire system. Techniques such as distributed MPC (90, 91), cooperative MPC (92), and agent-based control (93) have been proposed to provide coordination between subsystem controllers. Recent works (94) have used concepts from network theory to detect the optimal decomposition of subsystems for decentralized control strategies.

7.2. Control of Intensified Processes

Process intensification encompasses developments in process design or operation that lead to cleaner, smaller, and more energy-efficient technology (95, 96). It can be viewed as a limit case of process integration [i.e., as the flow rates of recycle streams tend to infinity (97)]; this relationship is depicted in **Figure 5**. Intensified processes thus present similar (or greater) control challenges as integrated processes: complex nonlinear behavior, strong interdependencies, and fewer degrees of freedom. In addition, many intensified process designs create strong driving forces by miniaturizing unit operations, introducing the additional control challenge of fast dynamics/small time constants. Research in the control of intensified processes generally follows the paradigm of first systematically identifying avenues for process intensification (i.e., process design) (98) and, second, establishing the appropriate control strategies, using, e.g., an operability analysis (99, 100).

A common theme in process intensification is multifunctional units, or combining the functionality of two or more conventional unit operations into a single physical device (101). For example, reaction and separation can be carried out concomitantly, such as in the case of reactive distillation. Reactive distillation columns pose a challenging control problem owing to nonlinearity/steady-state multiplicity and dynamic interactions; advanced control strategies are needed as a result

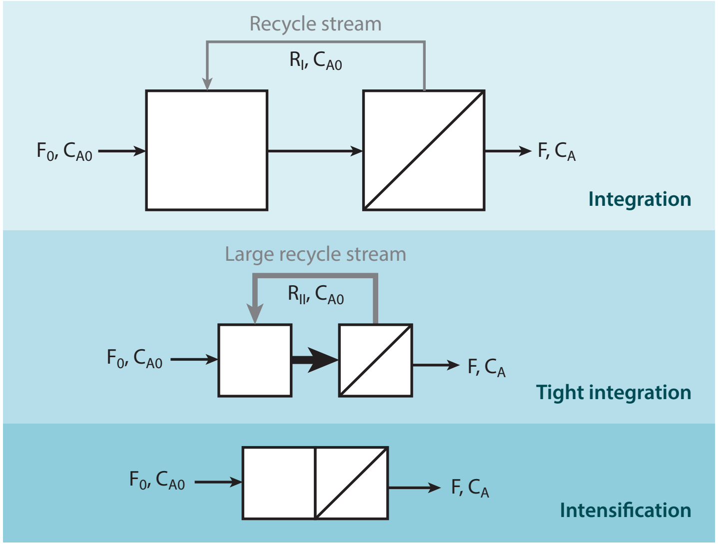

Figure 5

Conceptual reaction–separation–recycle process configurations illustrate the challenges of process control (loss of degrees of freedom) associated with tight process integration and process intensification. Figure adapted with permission from Reference 97; copyright 2015 Elsevier.

(102, 103). The dividing-wall column (DWC) is another case of an intensified, multifunctional unit (performing a ternary separation in a single column) that improves energy efficiency by advanced heat integration. Advances in MPC have enabled operation of DWCs closer to the optimal point in terms of energy efficiency (104), but deployment of DWCs remains limited by control challenges (105–107).

Dynamic process intensification (108) can yield substantial energy-efficiency improvements. Specifically, dynamically intensified process units are designed to operate at a cyclic steady state that exhibits more economically advantageous (i.e., lower energy use) time-averaged behavior compared with a unit having the same production characteristics but operated at steady state (109, 110). Process control plays a prominent role in the operation of dynamically intensified systems by (*a*) imposing the cyclic behavior and (*b*) ensuring the key variables, such as product purity, are kept at their (time-varying) target values at all times.

7.3. Integrated Design and Control

The control challenges associated with process integration and intensification have motivated research on the simultaneous (optimal) design of process units and their operating/control policies (111–113). The explicit integration of design and control calculations attempts to reconcile two competing interests: economic/energy efficiency and process controllability. For example, maximizing thermodynamic reversibility (i.e., minimal entropy production) improves the energy efficiency of a process but requires minimal driving forces (112) that lead to control challenges (e.g., saturation). The resulting multi-objective, mixed-integer dynamic optimization problems are computationally challenging to solve [especially when the physical process models are spatially distributed (114)]; solution methods typically rely on sequential (115) or simultaneous (116) procedures. Integration of design and MPC has also been proposed using explicit MPC (117).

However, although producing controllable plant designs is an important issue, surveys of current practices have revealed that the primary goal of the chemical industry is to obtain the best design from an economic perspective and that process control is typically addressed once the design is complete (118).

8. DISCUSSION AND CONCLUSIONS

Energy use will remain a prominent concern in the process industries; in this work, we attempted to summarize the (direct and indirect) ways that process control systems can support energy efficiency. From a practical perspective, bulk chemicals plants and refineries have by now almost fully adopted the MPC paradigm; in their case, controller maintenance will likely account for most of the control-related work done toward improving energy/economic efficiency. Other energy-intensive process industries that continue to rely on conventional control setups may significantly benefit from advanced control solutions like MPC and EMPC.

The process systems engineering community must continue to innovate to support the evolving needs of chemical production. One topic that merits investigation is the integration of process control and equipment monitoring. Equipment degradation (e.g., fouling, deactivation, mechanical wear) is a primary source of efficiency loss, because it causes the process to operate away from its (optimal) design conditions. At present, equipment maintenance typically follows a fixed schedule (or is carried out when performance has degraded so severely that it may cause a costly shutdown). We posit that process systems researchers are uniquely well-positioned to use the big data sets collected by process historians to actively monitor equipment condition and inform proactive maintenance policies.

Installation of new sensors will be critical to improve energy efficiency: Better sensing provides better information that can be used to improve control and reduce wasted energy. These sensors are often expensive, however, especially when process conditions are severe. Existing process models and soft sensors can be used to make the best use of scarce resources/limited sensing capabilities, including across multiple units. Future systems and devices should be designed explicitly for ongoing monitoring of energy efficiency and performance, e.g., by directly measuring/inferring energy flows where possible.

We also suggest cooperation across businesses as an emerging avenue for reducing energy waste. Technological advances in data collection and information exchange make possible enhanced coordination between energy/utility suppliers and users. As an example, a steel mill can communicate its oxygen demand forecast to an upstream air separation plant. The air separation plant can then operate more efficiently by increasing the production of gas product when demand is high (i.e., avoiding unnecessary vaporization of energy-intensive liquid products owing to misalignment of demand and supply) (119).

At the policy level, it will be necessary to explore new energy pricing strategies and incentives. Organizations will increasingly be able to directly incorporate energy consumption/sustainability metrics in their operational strategies. However, policy shifts (in the form of incentives, taxes, and regulations) may be necessary to fully align process economics with energy-efficiency goals.

DISCLOSURE STATEMENT

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