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A tutorial review of economic model predictive control methods

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ABSTRACT

An overview of the recent results on economic model predictive control (EMPC) is presented and discussed addressing both closed-loop stability and performance for nonlinear systems. A chemical process example is used to provide a demonstration of a few of the various approaches. The paper concludes with a brief discussion of the current status of EMPC and future research directions to promote and stimulate further research potential in this area.

1. Introduction

Optimal operation and control of dynamic systems and processes has been a subject of significant research for many years. Important early results on optimal control of dynamic systems include optimal control based on the Hamilton–Jacobi–Bellman equation [16], Pontryagin's maximum principle [135], and the linear quadratic regulator [84]. Within the context of the chemical process industries, room for improvement in process operations will always exist given that it is unlikely for any process to operate at the true or theoretically global optimal operating conditions for any substantial length of time. One methodology for improving process performance is to employ the solution of optimal control problems (OCPs) on-line. In other words, control actions for the manipulated inputs of a process are computed by formulating and solving a dynamic optimization problem on-line that takes advantage of a dynamic process model while accounting for process constraints. With the available computing power of modern computers, solving complex dynamic optimization problems (e.g., large-scale, nonlinear, and non-convex optimization problems) on-line is becoming an increasingly viable option to use as a control scheme to improve the steady-state and dynamic performance of process operations.

The process performance of a chemical process refers to the process economics of process operations and encapsulates many objectives: profitability, efficiency, variability, capacity, sustainability, etc. As a result of continuously changing process economics (e.g., variable feedstock, changing energy prices, etc.), process operation objectives and strategies need to be frequently updated to account for these changes. Traditionally, economic optimization and control of chemical processes has been addressed in a multi-layer hierarchical architecture (e.g., [106]) which is depicted in Fig. 1. In the upper-layer called real-time optimization (RTO), a metric usually defining the operating profit or operating cost is optimized with respect to up-to-date, steady-state process models to compute optimal process set-points (or steady-states). The set-points are used by the lower-layer feedback process control systems (i.e., supervisory control and regulatory control layers) to steer the process to operate at these set-points using the manipulated inputs to the process (e.g., control valves, heating jackets, etc.). In addition to the previously stated objective, process control also must work to reject disturbances and ideally, guide the trajectory of the process dynamics along an optimal path.

The supervisory control layer of Fig. 1 consists of advanced control algorithms that are used to account for process constraints, coupling of process variables, and processing units. In the supervisory control layer, model predictive control (MPC) (e.g., [116,109,140]), a control strategy based on optimal control concepts, has been widely implemented in the chemical process industry. MPC uses a dynamic model of the process in the optimization problem to predict the future evolution of the process over a finite-time horizon to determine the optimal input trajectory with respect to a specified

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performance index. Furthermore, MPC can account for the process constraints and multi-variable interactions in the optimization problem. Thus, it has the ability to optimally control constrained multiple-input multiple-output nonlinear systems. The conventional formulations of MPC use a quadratic performance index, which is essentially a measure of the predicted deviation of the error of the states and inputs from their corresponding steady-state values, to force the process to the (economically) optimal steady-state. The regulatory control layer includes mostly single-input single-output control loops like proportional-integral-derivative (PID) control loops that work to implement the computed control actions by the supervisory control layer.

The overall control architecture of Fig. 1 invokes intuitive time-scale separation arguments between the various layers. For instance, RTO is executed at a rate of hours-days, while the regulatory control layer computes control actions for the process at a rate of seconds-minutes (e.g., [11,147]). Though this paradigm has been successful, we are witnessing the growing need for dynamic market-driven operations which include more efficient and nimble process operation [7,81,150,36]. To enable next-generation operations, novel control methodologies capable of handling dynamic optimization of process operations must be proposed and investigated. In other words, there is a need to develop theory, algorithms, and implementation strategies to tightly integrate the layers of Fig. 1. The benefits of such work may be transformative to process operations and usher in a new era of dynamic (off steady-state) process operations.

To this end, it is important to point out that while steady-state operation is typically adopted in chemical process industries, steady-state operation may not necessarily be the economically best operation strategy. The chemical process control literature is rich with both experimental and simulated chemical processes that demonstrate performance improvement with dynamic process operation (see [41,94,13,151,149,158,159,131,133,132,153, 23,97,126,24,105,152], and the numerous references therein for results in this direction). In particular, periodic operation of chemical reactors has been perhaps the most commonly studied example (e.g., [151]). Periodic control strategies have also been developed for several applications (for instance, [97,126,23,149,133]). Several techniques have been proposed to help identify systems where performance improvement is achieved through periodic operation which mostly include frequency response techniques and the application of the maximum principle [41,9,21,8,66,158].

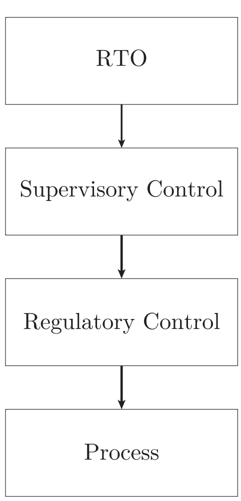

Fig. 1. The traditional paradigm employed in the chemical process industries for process optimization and control.

In an attempt to integrate economic process optimization and process control as well as realize the possible process performance improvement achieved by consistently dynamic, transient, or time-varying operation (i.e., not forcing the process to operate at a pre-specified steady-state), economic MPC (EMPC) has been proposed which incorporates a general cost function or performance index (i.e., objective function) in its formulation [72,56,141]. The cost function may be a direct or indirect reflection of the process economics. However, a by-product of this modification is that EMPC may operate a system in a possibly time-varying fashion to optimize the process economics (i.e., may not operate the system at a specified steady-state or target). The rigorous design of EMPC systems that operate large-scale processes in a dynamically optimal fashion while maintaining stability (safe operation) of the closed-loop process system is challenging as traditional notions of stability (e.g., asymptotic stability of a steady-state) may not apply to the closed-loop system under EMPC. It is important to point out that the use of OCPs with an economic cost function is not a new concept. In fact, MPC with an economic cost is not new either (e.g., one such EMPC framework was presented in [72]). However, closed-loop stability and performance under EMPC has only recently been considered and proved for various EMPC formulations.

This article attempts to organize the recent theoretical developments on EMPC. Further explanation of the theory is given where possible in an attempt to make the theory tractable and accessible to even a beginning graduate student working in the area of process control. The remainder of the paper is organized as follows. In the next section, the preliminaries are presented which include the notation used throughout this work, the class of nonlinear process systems considered, as well as a more thorough description of real-time optimization and model predictive control. The subsections on RTO and MPC are not meant to be comprehensive, but rather, are presented to provide some historical background on the challenges addressed in this area. The third section examines closed-loop stability under EMPC and outlines the various types of constraints and modifications to the objective function that have been presented to guarantee some notion of closed-loop stability. The fourth section discusses closed-loop performance under EMPC. Various EMPC formulations are subsequently applied to a chemical process example in the fifth section. An overall discussion and analysis is provided in the sixth section which attempts to provide our perspective on the current status of EMPC. Lastly, the review concludes with a discussion of future research directions.

2. Preliminaries

2.1. Notation

The operator $|\cdot|$ is used to denote the Euclidean norm of a vector, while the operator $|\cdot|_Q^2$ is used to denote a square of a weighted Euclidean norm of a vector where Q is a positive definite matrix (i.e., $|x|_Q^2 = x^TQx$). The symbol $S(\Delta)$ denotes the family of piece-wise constant functions with period Δ. A continuous function $\alpha : [0, a) \rightarrow [0, \infty)$ belongs to class $\mathcal{K}$ if it is strictly increasing and satisfies $\alpha(0) = 0$ and belongs to class $\mathcal{K}_\infty$ if $a = \infty$ and α is radially unbounded. A continuous, scalar-valued function, $\beta : \mathbb{R}^{n_x} \rightarrow \mathbb{R}$ is positive definite with respect to x_s if $\beta(x_s) = 0$ and $\beta(x) > 0$ for all $x \in \mathbb{R}^{n_x} \setminus \{x_s\}$. The symbol Ω_ρ denotes a level set of a scalar function $V(\cdot)$ (i.e., $\Omega_\rho = \{x \in \mathbb{R}^{n_x} | V(x) \leq \rho\}$). The set operators $\oplus$ and $\ominus$ denote the following set operations:

$$\mathbb{A} \oplus \mathbb{B} = \{c = a + b | a \in \mathbb{A}, b \in \mathbb{B}\}$$
$$\mathbb{A} \ominus \mathbb{B} = \{c | \{c\} \oplus \mathbb{B} \subseteq \mathbb{A}\}$$

or in other words, $\mathbb{A} \oplus \mathbb{B}$ is a set with elements constructed from the addition of any element of the set $\mathbb{A}$ with any element of the

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