

Pablo Antonio López-Pérez, Omar Jacobo Santos Sánchez, Liliam Rodríguez Guerrero, and Patricio Ordaz

# Advanced Control Methods for Industrial Processes

Modeling, Design, and Simulation of Emerging Systems in Real Time



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Edited by

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#### Preface

This book presents recent research advances in emerging topics for the application of advanced control to real-time system. The book includes robust solutions to important theoretical issues and also applied contributions to the design of complex systems. The book's novel structure completely describes the most important advanced control optimization algorithms at the theoretical and experimental level.

Specifically, we focus on optimizing unit operations used in different processes in emerging areas through advanced control techniques. Furthermore, the book's approach is based on understanding electrical, physical, chemical, industrial food dehydrator and biochemical systems, using mathematical modeling, in terms of inputs, outputs and simulation and experimental platforms that are implemented in most systems of modern advanced control engineering. Furthermore, this book has been developed from the perspective of advanced control engineering theories that can be applied to experimental platforms. A solid grounding is provided in traditional control techniques, followed by detailed studies of modern control techniques such as real-time and in silico systems.

This book also has several practical exercises. MATLAB, LabVIEW toolbox, and other open-source software is integrated as complementary material, which allows readers to quickly move from a simulation environment to an experimental one. The book also includes interfaces for the advanced control systems: between controllers and systems theory, between different levels, and between operators and systems. In addition to working principles and operation mechanisms, this book emphasizes the practical issues of components, devices and hardware circuits, providing specification parameters, installation procedures, calibration and configuration methodologies necessary for engineers when putting theory into practice for the advanced control techniques.

This book develops advanced discrete-time and, in some cases, continuous control techniques that require real-time execution when connected to a real experimental plant, that is, the controller task must be activated at fixed points in time and finished within a certain time. Therefore, we propose that the control engineer should be aware of the effects resulting from the finite processing power of the hardware controller and I/O units. Computational delays and jitter must be carefully considered when designing a real-time system because they introduce variable time delays into

the system, leading to loss of control quality or even instability and severe physical damage to the system controlled. Part I of this book describes basic implementation techniques for such simple systems, including a discussion of numerical integration algorithms suitable for real-time execution and a stability-convergence test of the controller proposal. Part II complements the theoretical part via practical cases with real-time application. In general, we organized the book with interesting structures that include a complete description of the most important advanced control optimization algorithms to level theoretical and experimental, as well as several practical exercises. Finally, it integrates the development of new sensor technology that provides strong technical support for the optimal operation and coordinated control of an integrated energy system (IES). The book is divided into two parts with eight chapters in total.

- Part I (Chapters 1 and 2) includes a general overview of the comparative study of different classical theories for process control. This part focuses on control theory and the behavior of dynamical systems. When one or more output variables of a system need to follow a certain reference over time, a controller manipulates the inputs of a system to obtain the desired effect on the system's output. The above is based on an input and output approach. The overall aim is to present sensors, instrumentation, and control and their uses within measurement systems as an integrated and coherent subject applied to advanced control theories. The advances in systems' technology have radically altered the control design options mainly in implementation, and low-cost design capability can be obtained because of the widespread availability of inexpensive and powerful digital processing platforms and high-speed analog I/O devices. We focus on systems described with ordinary differential equations for linear and nonlinear processes. In addition, we emphasize that most ideas, methods, and results presented here extend to a more general setting, which leads to very important technical developments.
- Part II (Chapters 3 to 8) introduces the theory of linear and nonlinear control applied to industrial processes and research. In practice, the development of process control engineers generally apply control tools to their processes focuses on the dynamics of bioprocesses, which are often complex and slow. For mechanical or electrical systems and because of the above, new advanced control strategies are rarely modeled and implemented in real time necessary in the processes. Part II focuses on modelling and controlling different types of processes, as well as designing and monitoring different types of sensors, valves, feedback loops, sequences, and constraints that work together to automate a given process. An approach based on in silico systems, modeling, and simulations, combined with real-time applications, is developed. For example:
  - 1. A new control strategy is applied and designed based on a theoretical framework of Lyapunov stability.
  - **2.** Prediction-based control delay systems are designed with one state delay and two delayed inputs.

- **3.** Nonlinear stabilization for a class of time delay systems based on the wellknown control Lyapunov-Krasovskii functional using Sontag's universal formula.
- **4.** Robust and adaptive proportional-integral (PI) control schemes are designed.
- 5. A discrete optimal control law for an input variable is executed in real time.

The examples are implemented in experimental platforms such as Arduino and academic MATLAB communication between LabVIEW and hardware devices (reactors, valves, and sensors) through an online interface design in LabVIEW. Data acquisition and control is performed in cRIO-9030-NI from actuators and a coupled connection, via digital implementation in LabVIEW and MATLAB. In addition, a PI controller optimally was tuned into a Honeywell DC10440 industrial PID. finally, monitoring is based on IoT that analyzes the system in real time based on related IoT security sensors to detect risk factors. The above is applied to the emerging topics such as the following:

- 1. Design of a nonlinear controller to regulate hydrogen production in a microbial electrolysis cell (MEC) and monitoring energy production in a microbial fuel digester (MFD)
- 2. Optimal control approach applied to a fed-batch reactor for wastewater treatment plants
- **3.** A coupled tank process modeled as a two-in-two-out (TITO) system with inherent delay due to the tube length, from actuators and coupled connection
- 4. Control applied to a tomato dehydrator with the CLKF approach
- 5. Control implemented in a heat exchanger to regulate the temperature of a fluid (distilled water) by transferring heat between a thermal resistance and a spiral-shaped metal conduit through which the fluid circulates

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Part I

**Classical and Advanced Control Theory: Simulation and Examples** 

## **Field Elements of Classic Control Systems**

After reading this chapter, you should be able to understand that:

- The chapter mainly compares different classical theories regarding process control.
- We will focus on systems described in terms of ordinary differential equations for linear and nonlinear processes.
- In addition, it must be emphasized that most ideas, methods, and results presented here do extend to this more general setting, which leads to very important technical developments.

## 1.1 The Principles of Control (Industry 5.0)

Industry 5.0 is a continuation of Industry 4.0 with the objective of introducing humans (human intelligence) as the main axis of industrial production processes. Furthermore, innovation in production processes is human-oriented and highly customizable based on technological advances and high productivity of systems. However, the concept of Industry 5.0 is not accepted so far by corporations and industries but is promoted by researchers because, today, the industrial situation challenges are still congenital to Industry 4.0 and the era of digitalization. Industry 4.0 encourages high manufacturing efficiency and quality, and focuses on near novelty, techno-economic development, and industrial technology progress [1, 2]. Thus, Industry 5.0 is a prolongation and chronological extension of Industry 4.0 [3]. Industry 4.0 has restrictions with regard to industrial sustainability security, as it emphasizes on the productivity and flexibility of manufacturing through digitalization and technologies and integration of data from operations and business activity. The present manufacturing toward evolution of Industry 4.0 operations allows for better-quality productivity through information-driven automation, not only by infrastructure, but also by introducing more advanced monitoring, modeling, sensors, measurements, and control strategies in real time [4, 5]. One of the main advantages of Industry 4.0 is big data, which relates to large sets of processes and manufacturing data collected by sensors and greater visibility of

#### 1

#### 4 1 Field Elements of Classic Control Systems

process analytical technologies in the manufacturing operations. The improvements obtained from such a proactive, predictive feed-forward control approach can exceed the incremental yield progresses that corporations seek [6–9]. Furthermore, these data can be used for optimization purposes by applying innovative big data analytics. Machine learning (ML), a branch of artificial intelligence, is one of the ways to accomplish this [10] (see Figure 1.1).

Technological processes consist of handling, working, refining, combining, and manipulating materials and fluids to produce cost-effective end products. These processes can be precise, demanding, and potentially hazardous. Small changes in a process can have a large impact on the end result [14, 15]. Variations in proportions, temperature, flow, turbulence, and many other parameters are to be carefully and consistently controlled to consistently produce the end product of the desired quality with a minimum of raw materials and energy. Instrumentation provides various indications used to operate a technological process [16-18]. In some cases, the operator records these indications for use in the operation of the process. The information recorded helps the operator evaluate the current condition of the process and take action if the conditions are not as expected. Requiring the operator to take all of the necessary corrective actions is impractical, or sometimes impossible, especially if a large number of indications are to be monitored. For this reason, most technological processes are controlled automatically once they are operating under normal conditions [19, 20]. The main role of process control was to contribute to safety, minimize external perturbation influence, and optimize processes by preserving process variables near the desired values. As the processes become larger in scale-up or behavior complex, the role of process automation has become more important.



Figure 1.1 The concept of Industry 5.0. Adapted from Borchardt et al. [11].



# **Figure 1.2** The timeline of industrial revolutions. Adapted from Madsen and Berg [12] & Cohen and Singer [13].



# **Figure 1.3** The timeline of industrial revolution's pyramid of automation. Adapted from López-Pérez et al. [7], Lucizano et al. [23], Wollschlaeger et al. [24], Martinez et al. [25].

Industrial revolution

#### 6 1 Field Elements of Classic Control Systems

Today automation has taken over process control purposes, which means that operatives are assisted by a distributed control system, which communicates with the instruments in the real process. Process control is a combination of the statistics and engineering areas that deal with the sensors, designs, and algorithms for controlling a process. The aim of process control is to have it behave in a desired value. This includes the processes that are appealing, more accurate, more reliable, or more economical [21, 22] (see Figure 1.2).

In different manufacturing industries, advanced process control systems (APC) have become a nonnegotiable necessity for any manufacturing operation, which allows progress in the automation, understanding, and use of complex systems. APC incorporates a variety of model-based software system technologies, as well as stochastic and metaheuristic systems (see Figure 1.3). Currently, APCs provide supervisory control, bridging the gap between basic controls and overall process improvement, allowing the process to be cost-effective and of sustainable quality and operational safety aligned with Industry 4.0 and 5.0 [26–28].

## 1.2 Field Elements of Classic and Modern Control Systems

Modern advanced control techniques are model-based in data and look to apply mathematical optimization tools to optimize the performance based on future predictions and conditions. The necessary components and fields for this background are as follows:

- i. A dynamic model.
- ii. Estimator that converts measured process variables into estimates of unmeasured states and/or parameters.
- iii. An algorithm that computes the optimal control action based on model predictions (multi-objective optimization function or Pareto and constraint set).
- iv. Methods that restrict the model to be linear.
- **v.** Methods that require a very large amount of data to provide any statistical guarantees.
- vi. Methods for uncertainty descriptions are not necessarily accurate or related to physical quantities.
- vii. Improving system performance in terms of functionality, security, energy efficiency, environmental impacts, and costs.
- viii. Virtual sensors in the industry manages to optimize the operational performance, safety, functionality, and reliability of the bioprocess.
  - ix. Monitoring, diagnosis, and control could be provided more reliably and robustly using physical sensors.
  - **x.** Embedded system is any device that is made up of a programmable computer (microprocessor or microcontroller).
  - xi. Computer hardware.
- xii. Operating system in real time.
- xiii. Efficiency and quality in manufacturing.
- xiv. Hyper-competitive manufacturing sector.
- xv. Internet of Things (IoT).

- xvi. Human-machine interface and supervisory control and data acquisition (SCADA).
- xvii. Basic regulatory control, advanced regulatory control, multivariable, modelbased control, constrained economic optimization, multi-unit constrained economic optimization, first principle economic optimization (RTO), steadystate process model, and economic information (e.g., prices and costs) performance Index to be maximized (e.g., profit) or minimized (e.g., cost) [29, 30].

#### 1.2.1 Advantages

- Reducing operational costs to secure tribal knowledge.
- Easy maintenance as it is not a compact system. In the case of breakdowns, the affected component is easily replaced without completely replacing the entire system.
- They have small size, so they easily adapt to any industrial application without requiring a large workspace.
- It is adaptable. Any necessary module can be integrated.
- They consume minimum energy, which causes the battery life to be extended.
- They give high performance in processing data at high speed and in real time.

#### 1.2.2 Disadvantages

- They are specific operating systems.
- The software of an embedded system presents some restrictions such as small amounts of memory (generally, in the order of kB).
- Limited processing capabilities (generally, the speed of the processors does not exceed the order of MHz).
- Limits the consumption of instant energy whether in execution state or not.
- They may present cybersecurity risks because they feature weak encryption.
- Data shared between two devices can be easily intercepted and decrypted.

For example: data acquisition systems and system monitor parameters such as  $O_2$ ,  $CO_2$ , temperature, flow, humidity, and pH based on the sensors that will collect data and the controllers to correspond to the set points of the variables. The measured data have the potential to practice another improved software tool for the estimation of variables and parameters from process data [31–33].

### 1.2.3 Why Control and Monitor?

The measurement of variables in processes is a necessary requirement to overcome following concerns:

- i. To know internal behaviors.
- ii. Fault diagnosis.
- iii. Monitoring.
- iv. Visualization of critical variables.
- v. Processing is subject to disturbances.

- 8 1 Field Elements of Classic Control Systems
  - vi. Nonlinear systems.
  - vii. Unstability.
  - viii. Maintain productivity.
  - ix. Quality standards.

In addition:

- i. Absence of trusted devices.
- ii. Time delays.
- iii. Errors in the measurement system.
- iv. High device costs.
- v. Measurement conditions.
- vi. Unavailability of sensors.

Nowadays, process and system control theory can be divided into two areas: classical methods and modern control theory methods. The main differences between these groups focus on the representation, design, and operation of dynamic systems or data management in real time, at-line, offline, online, and in-line. Figure 1.4 briefly summarizes the differences between classical and modern control theory methods [7].

General characteristics of classical control methods: Classical control methods are not able to incorporate constraints logically ascending from industrial control problems and have optimization missing complete performance. The most common



Transform domainPID Input-output (I/O) Z transform Laplace Changing time-domain ODE's

Complexities of ODE Multiple-output multiple-input Lyapunov theory sliding-mode control

**Figure 1.4** Properties' comparison of classical and modern control methods. Adapted from Jha et al. [34], Drgo na et al. [35], Holaza et al. [36].

example of classical control methods is the proportional integral derivative (PID) controller, which accounts for more than 95% of the control and automation applications today, mainly thanks to its simple implementation with relative efficiency [37]. Main advantage of state–space representation is the preservation of the time-domain attractiveness, where the response of a dynamical system is a function of many inputs, previous system states, and time, presently

$$y = f(x, u, t). \tag{1.1}$$

Industrial processes often experience nonlinear behaviors that may include output multiplicity, bifurcations, chaos, unstable dynamic response to disturbances, and changes in system parameters; all these phenomena can lead to instability and, ultimately, affect the yield of production. For this reason, the application of traditional linear controllers is limited since they are not able to cope with the high nonlinear behavior of industrial processes. Aside from this, incidental external and internal disturbances in a manufacturing process lead to disappointment and can be a costly and annoying problem for any engineer. Regulatory control is the main strategy for attaining the basic operational requirements in manufacturing processes. The regulatory control has been performed through classical PID feedback controllers by considering the easiness of its practical implementation and satisfactory performance within common industrial practice [38]. Controllers employed range from simple on–off type to proportional (P), integral (I), derivative (D), and PID controls and expert systems. A scheme of typical control is shown in Eq. (1.2).

$$u(t) = \underbrace{K_p e(t)}_{\text{Proportional}} + \underbrace{K_i \int e(t) dt}_{\text{Integral}} + \underbrace{K_d \frac{d}{dt} e(t)}_{\text{Derivative}}$$
(1.2)

The  $K_P$ ,  $K_d$ , and  $K_i$  are the tuning parameters of the controller that can be adjusted by varying the dynamics of the control loop. Feed rates can also be adjusted based on an optimal objective function derived online or offline. The objective function targets to increase productivity or maximize operating profits [39].

In relation, other feedback controllers have been proposed for improving the dynamic performance of the manufacturing processes: among them, the adaptive controllers can modify some parameters in the control's structure to maintain a satisfactory process operation [40]. Controllers designed to combat input disturbances and noisy measurements have been presented in the literature for several years within the following frameworks: sliding-mode theory, observer-based I/O linearizing controllers, and optimal controllers [41]. On the other hand, most of the controllers designed for the aforementioned existing outputs are complicated; therefore, they are difficult to perform in real applications. In fact, how to design a simple and physical controller to perform the control problems of complex chaotic systems is also important both in theory and in application. One of the most important drawbacks of the advanced control designs is their complexity for practical applications and the complete understanding by the plant engineers. Thus, alternative control structures must be simple enough to avoid the abovementioned existing outputs are tively, most of the controllers designed in the aforementioned existing outputs are

#### **10** 1 Field Elements of Classic Control Systems

complicated; therefore, they are difficult to perform in real applications. Therefore, the alternative control structures must be simple enough to avoid the abovementioned drawback [42, 43].

Once the information is in the supervision and monitoring equipment, not only is interaction with the user achieved through graphics, alarm signals, report generation, and global analysis of the plant, but it can also directly influence the dynamic behavior of the system variables through programming of observers, filters, virtual sensors, among other components that are incorporated into the plant [44]. Supervision achieves the reconfiguration of system parameters through the controller, executing a set of actions to bring the process to its normal operation using model-based self-tuning methods or without mathematical knowledge of the process, among others. This constitutes a crucial difference in relation to monitoring that only covers detection and diagnosis and sometimes those systems that undertake only surveillance tasks and have been mistakenly called supervision systems. Finally, the last n levels of the pyramid, manufacturing execution system planning, and enterprise resource planning are manufacturing execution systems that organize the resources necessary to execute the plant's production plan that covers raw materials, order of priorities, change of production instructions, the controllers, and measurement interval of the sensors, among others. Therefore, there is a strong financial inspiration to develop the finest control scheme that would facilitate rapid startup and stabilization of manufacturing processes subject to redundant disturbances. In the control literature, regardless of the considerable progress in APC proposals such as sliding-mode control, model predictive control, and internal model control, PID controllers are still widely employed in industrial control systems because of their structural simplicity, reputation, robust behavior, and easy implementation (see, Figure 1.5). Along with the system's stability, it also satisfies chief performance such as smooth reference tracking, efficient disturbance rejection, and measurement of noise attenuation criteria [45-47].

For a process which is operating satisfactorily, the variation of product quality falls within acceptable limits. These limits normally correspond to the minimum and maximum values of a specified property. Normal operating data can be used to compute the mean deviation and the standard deviations of a given process variable from a series of observations. The standard deviation is a measure for how the values of the variable spread around the mean. A large value indicates wide variations in the variable. Assuming the process variable follows a normal probability distribution, then 99.7% of all observations is to lie within an upper limit and a lower limit. This can be used to determine the quality of the control. If all data from a process lie within the limits, then it can be concluded that nothing unusual has happened during the recorded period, the process environment is relatively unchanged, and the product quality lies within specifications. On the other hand, if repeated violations of the limits occur, then the conclusion can be drawn that the process is out of control and that the process environment has changed. Once this has been determined, the process operator can take action to adjust operating conditions to counteract undesired changes that have occurred in the process conditions [48-51].



Figure 1.5 Classical and modern control theory.

## 1.3 Process Modeling in Control Systems Design

Mathematical model of a dynamic System is a set of equations that represent with a certain degree of accuracy the dynamics of the physical system. The model is generally described as an operator between the inputs and outputs of the system, or as a set of differentials (continuous case) and/or difference (discrete case) equations. Generally, when working with dynamic systems that are modeled by a finite number of coupled first-order ordinary differential equations, the state variables represent the "memory" that the dynamic system has of its past. Vector notation is usually used to write these equations compactly; the *n* first-order differential equations can be defined and rewritten as a vector differential equation of dimension n [52–55]. A thorough understanding of the time-dependent behavior of the technological processes is required to instrument and control the process. This, in turn, requires an appreciation of how mathematical tools can be employed in the analysis and design of process control systems. There are several mathematical principles that are utilized for automatic control. These are as follows:

- Physical, chemical, biological models, and empirical models.
- Simulation of dynamic models.
- Laplace transforms.
- Fitting dynamic models to experimental data [56-58].

**Dynamic system**: it is the one that generates data that change with the passage of time, that is, they possess certain dynamics. Dynamic systems are systems whose



**Figure 1.6** Dynamic system modules. Adapted from López-Pérez et al. [59, 60], Jongeneel and Moulay [61].

internal variables (state variables) follow a series of temporal rules (see Figure 1.6). They are called systems because they are described by a set of equations that are time-dependent, either implicitly or explicitly. Dynamic system classes:

- Isolated: they do not interact with their environment.
- Not insulated: interact with your environment.
- Natural: unaffected by human intervention.
- Artificial: created by man.
- Physics: they involve matter and energy.
- Not physical: thoughts.

**Black Box**: Black box is a system in terms of inputs and outputs. These models allow a global characterization of the model by disturbing its input to observe the variation or effect of said input on the states and parameters of the system at the output, that is to say: an identification, parametric sensitivity, and confidence interval of operation and parameters. Examples of some tools for the development of blackbox models are as follows:

- Support vector machines.
- · Partial least squares.
- Artificial neural networks.
- Fuzzy inference system.