

PART I

BACKGROUND AND FUNDAMENTALS

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CHAPTER 1

INTRODUCTION

This chapter is an introduction of the book. It briefly introduces background, motivation, and objectives of the research, followed by the contribution and organization of the book.

1.1 BACKGROUND AND MOTIVATION

Since we moved into the Industrial Age, most of the products used have been manufactured by machines and production lines. The manufacturing industry has changed much from the traditional sector, like steel and auto factory, to the semiconductor or IC industry in 1980s, and to the internet-based global manufacturing nowadays. Advanced manufacturing uses the so-called “advanced,” “innovative,” or “cutting-edge” technology to improve products and/or processes. The distinctions between traditional sectors of manufacturing and advanced manufacturing are in terms of volume and scale economies, labor and skill content, and intelligence added in the system.

In modern IC industry, the higher speed, the higher precision, and the higher intelligence have become common requirements to many of the processes involved, for example, epoxy/silicone dispensing (Li et al., 2007), curing process (Li, Deng, and Zhong, 2004; Deng, Li, and Chen, 2005), bonding/wiring process (Li and Zuo, 1999), and so on. Even in a traditional industry, like the forging press machine (Lu, Li, and Chen, 2012), the machine will seek help from an intelligence unit for meeting quality

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and economic constraints. Modern information technology can make a traditional system more advanced.

No matter how complex or advanced the manufacturing operation is, it always consists of basic actions offered by basic systems. These basic systems could be classified into the following three different categories.

- **The static system.** The performance is invariant over time, so it is discrete.
- **The dynamic system.** The performance is varying over time, so it is continuous.
- **The hybrid system.** It is a combination of the above two, which forms a hybrid system with discrete/continuous parameters, or a hybrid discrete/continuous system.

Design for advanced manufacturing is actually centered on the design and control of these basic systems, as the performance of every basic system is crucial to the overall performance of the manufacturing.

Since advanced manufacturing usually involves more complex system configuration and more advanced technologies, it will require a higher quality design of each basic system involved in the operation. However, unavoidable external variations in manufacturing operations, material properties, and a complex operating environment will result in an inconsistent performance of the system, which will be a big challenge to design for manufacturing. If these variations are not properly considered in product design, the degraded performance may result in a failure in operation (Caro, Bennis, and Wenger, 2005). Thus, robust performance, insensitive to all possible changes in demand, model uncertainties, and external disturbance, is one of the most important concerns in the design of any system.

In system design, robust design is the most important method commonly used to achieve robust performance. Its fundamental principle is minimizing the sensitivity of the performance to uncontrollable variations. Most of these approaches are for static systems, a few for dynamic systems. Furthermore, design and control are always separated in both academic research and industrial applications, which leads to few effective methods for the hybrid system.

The principal goal in this book is to develop effective design methods for fundamental systems existing in advanced manufacturing, including

1. novel robust design methods for both static and dynamic systems; and
2. robust design and control integration methods for the hybrid discrete/continuous system.

Though these methods are studied for basic systems in this book, they should be easily applied to any advanced manufacturing or production.

There are three different sets of variables that will appear in robust design.

- **Design variable (or control variable).** This is the controllable variable with its nominal value to be designed ideally between the upper and lower bounds. The variations around its nominal value are usually caused by poor manufacturing.

- **Uncertainty.** This usually includes parameter variation, noise, and model uncertainty. It cannot be adjusted by the designer, and thus is uncontrollable.
- **Performance.** This is the objective of the design and depends on the system model, design variable, and uncertainty.

Based on the above definition, we will introduce and discuss robust design and control integration in the rest of the chapter.

1.1.1 Robust Design for Static Systems

Robust design for the static system minimizes the influence of uncertainty on steady-state performance. Two typical robust design examples of the static system are introduced in Examples 1.1 and 1.2.

Example 1.1: Nonlinear system The damper structure widely exists in manufacturing industry and can be simplified as in Figure 1.1 (Caro, Bennis, and Wenger, 2005), where M and C_d are mass of the moving part and damping coefficient in the chamber, respectively. The excitation force $F(t)$ is assumed to be $F \cos(\omega \cdot t)$. The displacement will be $X(t) = X \cos(\omega \cdot t + \phi)$, where ϕ is the phase.

The performances X and ϕ can be expressed as follows:

$$X = \frac{F}{\omega \sqrt{C_d^2 + \omega^2 M^2}}, \quad \phi = \tan^{-1} \left(\frac{\omega M}{C_d} \right) \tag{1.1}$$

The objective is to keep the displacement and the phase at desirable values under the given excitation force. Due to manufacturing error, variations coming from fluid properties and the operating environment, there are large uncontrollable variations from the design variable M as well as the model parameter C_d in this system. Thus, this nonlinear system should be designed to be robust to these uncontrollable variations. ■

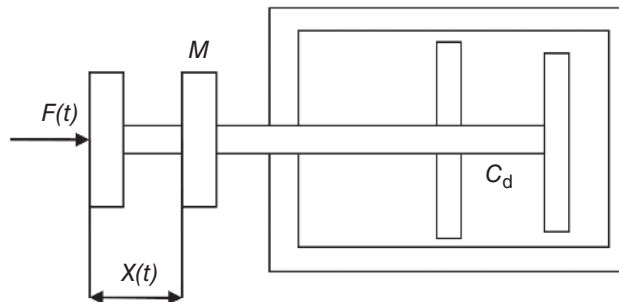


FIGURE 1.1 Damper

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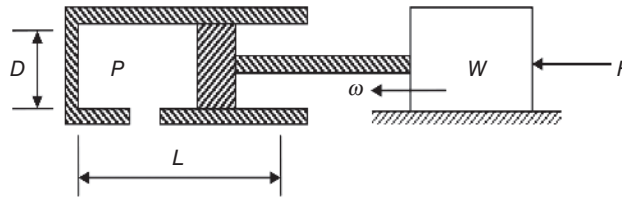


FIGURE 1.2 A pneumatic cylinder

Example 1.2: Partially unknown system The pneumatic cylinder, widely existing in manufacturing industry, is used to move a load of weight W along a horizontal surface, as shown in Figure 1.2. There exists the friction force F between the load and the surface, and the unknown disturbance force w is caused by other uncertain factors, such as leakage. The load is accelerated within a distance L to attain a steady-state velocity V . If the supply pressure is P , the actuator size D will be designed for a robust performance.

The performance V may be expressed as the sum of the known nominal model f and the model uncertainty Δf

$$V = f + \Delta f \tag{1.2}$$

with $f = \sqrt{\frac{gL(\pi D^2 P - 4F)}{2W}}$, $\Delta f = \sqrt{\frac{gL}{2W}} \left(\sqrt{\pi D^2 P - 4(F + w)} - \sqrt{\pi D^2 P - 4F} \right)$.

The nominal model f is derived from the force balance in the absence of the disturbance force w . The model uncertainty Δf is caused by unknown disturbance force w , and thus it, including its structure, is unknown as a black box to designers. For a desirable performance, a robust design is needed to properly handle all these uncertainties coming from the design variable D and the parameters W and F in the system. ■

In past decades, much effort has been dedicated to robust design of the static system. Design on this aspect can be classified into two main categories: the experiment-based robust design and the model-based robust design.

The experiment-based methods, as indicated in Figure 1.3a, design system robustness using experimental data. These methods have the advantage that no accurate system model is required. Typical examples include the Taguchi method (Ross, 1988; Taguchi, 1987, 1993) and the response surface method (Box, 1988; Tsui, 1992; Engel and Huele, 1996; Choi, 2005). All these methods are developed generally based on experiment data without process knowledge. Thus, the cost could be high if a large number of experiments are needed, and the method may not be accurate, especially for the strongly nonlinear system. Moreover, they cannot handle variations of design variables (Chen et al., 1996a). All these disadvantages may limit their applications and make it difficult to be applied for the nonlinear system described in Example 1.1, or the partially known system with variations of design variables described in Example 1.2.

The second class of methods is the model-based robust design, as shown in Figure 1.3b, which uses the model information to design the system robustness.

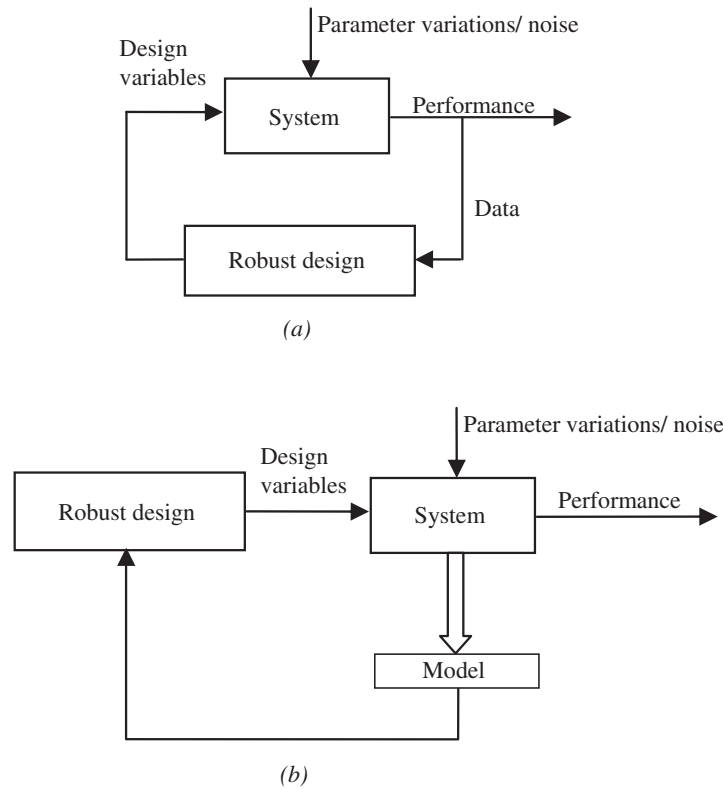


FIGURE 1.3 Traditional static robust designs: (a) experiment-based robust designs; (b) model-based robust designs

These kinds of methods are low cost and have high design accuracy compared with the experiment-based methods. In past decades, much effort has been dedicated to this class of robust design, which can be divided into two categories (Li, Azarm, and Boyars, 2006): probabilistic robust design approaches and deterministic robust design approaches.

The probabilistic robust design approaches use probabilistic information of variables, usually their mean and variance, to minimize the sensitivities of the performance (Li, Azarm, and Boyars, 2006). There are many authors that have contributed to the probabilistic approaches (e.g., Chen et al., 1996a, 2000; Al-Widyan and Angeles, 2005; Kalsi, Hacker, and Lewis, 2001; Yu and Ishii, 1998). The main shortcoming of the probabilistic approaches is that probability distributions must be known or presumed. Accurate knowledge of the distributions may be difficult to obtain and the presumed distributions may not be correct (Li, Azarm, and Boyars, 2006).

The deterministic robust design methods use a worst-case scenario approach to minimize the sensitivity. The robust design solutions are obtained using gradient information of variables, usually the Euclidean norm method and the condition number

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method (e.g., Ting and Long, 1996; Zhu and Ting, 2001; Caro, Bennis, and Wenger, 2005; Beyer and Sendhoff, 2007), to improve the system sensitivity. However, this gradient information may not be easy to obtain in practice.

In general, the model-based robust designs have the following limitations.

- They are mainly based on the approximate first- or second-order model derived by local linearization for the sake of simplicity and easy design. When the system is strongly nonlinear with larger uncontrollable variations, similar to Example 1.1, larger approximation errors may arise and make the design less effective.
- Ideally, the model-based design only works when the system model is available. Practically, an accurate model is often difficult to obtain due to complex boundary conditions, complexity of the process, or incomplete knowledge of the system. Thus, a realistic solution is to use the nominal model of the system, which is often built by assumption, idealization, and simplicity. This approximation will result in model uncertainty, like Δf in Example 1.2. This model uncertainty is usually neglected in the existing design, which makes the model-based approaches less effective because the ignored uncertainty will affect system performance.

Thus, it is very necessary to develop some new methods to

- design the strongly nonlinear system to be robust to larger uncontrollable variations; and
- design a system to be insensitive to model uncertainty as well as variations from parameters and design variables.

1.1.2 Robust Design for Dynamic Systems

Many manufacturing systems often work under open loop, without any external control, due to some physical and economic constraints. The dynamic performance of such systems fully depends on their own design. In contrast with the design of static systems, robust design for dynamic systems must consider dynamic properties. A typical example is as follows.

Example 1.3: Dynamic system The rotor system is another basic system used in manufacturing industry. It is depicted in Figure 1.4, where a shaft carries a single disk and rotates at constant velocity Ω . Since the rotating elements are symmetrical with respect to the rotor axis and the bearings are isotropic, this system is a nonconservative system (Seyranian and Kliem, 2003; Kliem, Pommer, and Stoustrup, 1998). For simplicity, the shaft is assumed massless with the elastic coefficient $k > 0$, a single disk has mass m with the external damping d_e and the internal damping d_i , and a bearing has mass m_b with the damping d_b and the elasticity k_b .

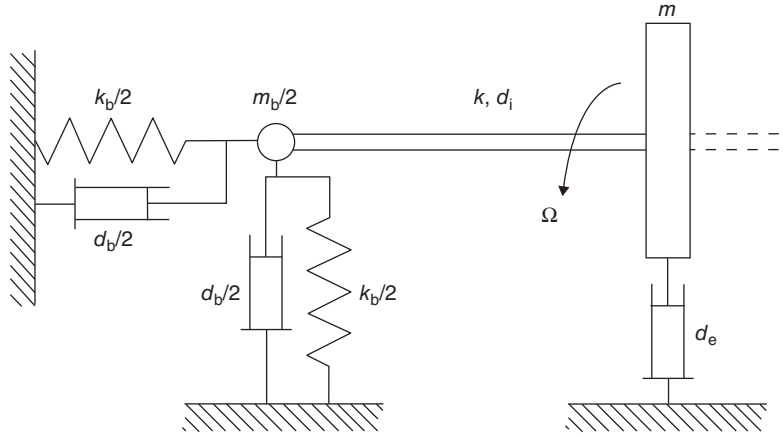


FIGURE 1.4 Physical model of a rotor system

The motion equation of the moving disk can be derived as

$$M\ddot{q} + D\dot{q} + Rq + \Delta f = 0 \quad (1.3)$$

with

$$M = \begin{bmatrix} m & 0 & 0 & 0 \\ 0 & m_b & 0 & 0 \\ 0 & 0 & m & 0 \\ 0 & 0 & 0 & m_b \end{bmatrix}, \quad D = \begin{bmatrix} d_e + d_i & -d_i & 0 & 0 \\ -d_i & d_b + d_i & 0 & 0 \\ 0 & 0 & d_e + d_i & -d_i \\ 0 & 0 & -d_i & d_b + d_i \end{bmatrix},$$

$$R = \begin{bmatrix} k & -k & d_i\Omega & -d_i\Omega \\ -k & k + k_b & -d_i\Omega & d_i\Omega \\ -d_i\Omega & d_i\Omega & k & -k \\ d_i\Omega & -d_i\Omega & -k & k + k_b \end{bmatrix} \Delta f = -M \begin{bmatrix} 0.01 \sin(p) & 0 & 0 & 0 \\ 0 & 0.01 \cos(p) & 0 & 0 \\ 0 & 0 & 0.005 & 0 \\ 0 & 0 & 0 & 0.005 \end{bmatrix} \dot{q}$$

where the parameter p has external uncertainty Δp at its nominal value p_0 . The model uncertainty Δf is usually caused by unknown resistance forces. The model uncertainty is unknown and is a black box to designers.

Let

$$x = \begin{bmatrix} \dot{q} \\ q \end{bmatrix}, \quad \Delta A = -M^{-1} \frac{\partial \Delta f}{\partial x} \Big|_{x=0} = \begin{bmatrix} \Delta A_{11} & 0_{4 \times 4} \\ 0_{4 \times 4} & 0_{4 \times 4} \end{bmatrix},$$

$$\Delta A_{11} = \begin{bmatrix} 0.01 \sin(p) & 0 & 0 & 0 \\ 0 & 0.01 \cos(p) & 0 & 0 \\ 0 & 0 & 0.005 & 0 \\ 0 & 0 & 0 & 0.005 \end{bmatrix}$$

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Since Δf and ΔA are unknown, the state–space equation for the rotor system is

$$\dot{x} = Ax \quad (1.4)$$

with the Jacobian matrix $A = A_0 + \Delta A$ and the nominal matrix $A_0 = \begin{bmatrix} -M^{-1}D & -M^{-1}R \\ I_{4 \times 4} & 0_{4 \times 4} \end{bmatrix}$.

The objective of the design is to determine design variables m and m_b to make the dynamic system stable and robust to the model uncertainty Δf and variations from parameter and design variables. ■

It is well known that the dynamic behavior of the engineering system, such as its stability, is closely related to the eigenvalues of the Jacobian matrix A . There are many studies to explicitly consider the dynamic stability using eigenvalue theory (Blanco and Bandoni, 2003; Kliem, Pommer, and Stoustrup, 1998; Mohideen, Perkins, and Pistikopoulos, 1997; Kokossis and Floudas, 1994). However, all these methods only make the real part of all eigenvalues smaller than zero, without consideration of influence from uncontrollable variations. Thus, the following problems need to be solved.

- All previous studies require the exact process model to be known without considering the influence of model uncertainty. Thus, they are difficult to apply to the partially unknown system in Example 1.3.
- Even if the process model is fully known, eigenvalue variation should be considered. Otherwise, the transient response may deviate from the desirable response (Liu and Patton, 1998). A robust transient response can only be achieved when all eigenvalue variations caused by parameter variations are small (El-Kady and Al-Ohaly, 1997). Thus, for guaranteed system stability, the eigenvalue variations should be minimal for the robust dynamic performance. Unfortunately, little attention has been paid to variations of the eigenvalues.

Thus, new design approaches should be developed not only to stabilize the system but also to minimize influence from parameter variations and model uncertainty.

1.1.3 Integration of Design and Control

As the manufacturing becomes more complex for higher quality, it becomes more difficult for traditional design and control to achieve the goal due to the hybrid nature of the process. The integration of system design and control might be needed, which is shown in the curing process in Example 1.4.

Example 1.4: Design and control of curing process The curing oven is a very important process in semiconductor packaging industry to provide a desirable temperature profile for curing epoxy resin and encapsulation molding compound that are distributed onto electronic components (Hisung and Pearson, 1997). The key requirement for high quality packaging is to maintain the uniform temperature for

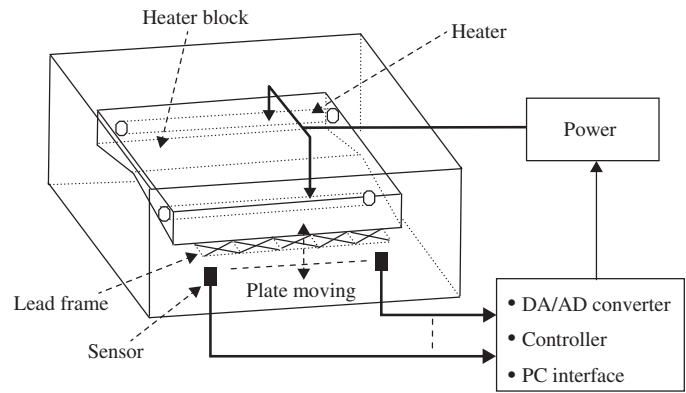


FIGURE 1.5 The studied curing system

the whole cured object and control it to follow the required temperature trajectory during the operation (Li, Deng, and Zhong, 2004).

As shown in Figure 1.5, a curing oven has a motion mechanism inside the chamber, which moves a working plate up and down to adjust the curing temperature for the IC placed on the lead frame (LF). A separate control system is also required to control the power of the heaters that are embedded in the heater block.

The finite difference method, a common modeling method for complex thermal processes, is used to model the curing process. The two-dimensional surface of the lead frame is discretized into many small zones by uniform intervals Δx and Δy , as shown in Figure 1.6. The coordinate of the zone (i, j) is $(x_i, y_j, 0)$. Each zone is assumed to have a uniform temperature, heat flux, and radiative property. Since the lead frame is thin enough, axial thermal gradient may be neglected.

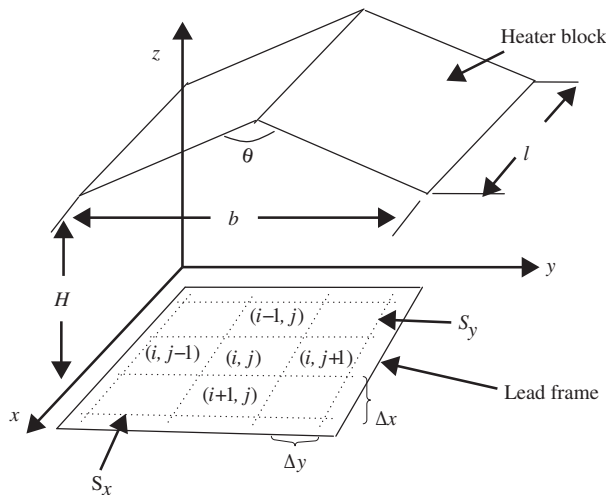


FIGURE 1.6 Geometric explanation

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The heat transfer model of every zone may be described as

$$m_{i,j}c \frac{dT_{i,j}(t)}{dt} = q_{i,j}^d + q_{i,j}^r + q_{i,j}^c + q_{i,j}^{wall} + q_{i,j}^{dist} \quad (i = 1, \dots, n; j = 1, \dots, p) \quad (1.5)$$

where

- $T_{i,j}(t)$ the temperature of the (i, j) zone at time t ;
- c and $m_{i,j}$ the specific heat coefficient and mass of the (i, j) zone, respectively;
- $q_{i,j}^d, q_{i,j}^r$, and $q_{i,j}^c$ heat flow rates coming into the (i, j) zone via conduction, radiation from heater block and convection from air, respectively; and
- $q_{i,j}^{wall}$ and $q_{i,j}^{dist}$ unknown heat from the chamber wall and disturbance respectively.

According to Fourier’s rule of heat conduction, heat conduction across a surface is expressed as

$$q_{i,j}^d = kS_x \left(\frac{T_{i+1,j}(t) + T_{i-1,j}(t) - 2T_{i,j}(t)}{\Delta x} \right) + kS_y \left(\frac{T_{i,j+1}(t) + T_{i,j-1}(t) - 2T_{i,j}(t)}{\Delta y} \right) \quad (1.6)$$

where k denotes thermal conductivity, and S_x and S_y are the cross-sectional area of every zone, as shown in Figure 1.6.

The radiative heat of a zone is

$$q_{i,j}^r = \epsilon S_{i,j} \{ F_{i,j}(d) u(t) - \sigma T_{i,j}^4(t) \} \quad (1.7)$$

where

- ϵ and σ the emissivity of the lead frame and Boltzmann constant, respectively;
- U the control variable that offers power to heaters; and
- $F_{i,j}(d)$ the view factor from the (i, j) zone to the heater block; it is a function of design variables $d = [\theta, l, b, H]$, where θ, l, b are curve angle, length, and breadth of the heater block, respectively, and H is distance between the LF and the heater block as shown in Figure 1.6.

Since the heat convection has a small effect compared with the other heat flux, it can be regarded as a disturbance. Define

$$\hat{w}_{i,j}(t) = \frac{1}{m_{i,j}c} (q_{i,j}^c + q_{i,j}^{wall} + q_{i,j}^{dist}) \quad (1.8)$$

Inserting Equations 1.6, 1.7, and 1.8 into Equation 1.5, the heat transfer model (Equation 1.5) may be rewritten as

$$\begin{aligned} \frac{dT_{i,j}(t)}{dt} = & \frac{kS_x}{m_{i,j}c} \left(\frac{T_{i+1,j}(t) + T_{i-1,j}(t) - 2T_{i,j}(t)}{\Delta x} \right) \\ & + \frac{kS_y}{m_{i,j}c} \left(\frac{T_{i,j+1}(t) + T_{i,j-1}(t) - 2T_{i,j}(t)}{\Delta y} \right) \\ & + \frac{\epsilon S_{i,j}}{m_{i,j}c} \{F_{i,j}(d)u(t) - \sigma T_{i,j}^4(t)\} + \hat{w}_{i,j}(t) \end{aligned} \quad (1.9)$$

Obviously, the model (Equation 1.9) has strong nonlinearity and model uncertainty. Moreover, this curing process must work over a large operating region (temperature range: 20–200°C) to track the required temperature profile.

Notwithstanding the complex dynamics of the process described above, the quality of production requires a uniform temperature distribution on the whole LF. The required overall performance cannot be measured directly in production due to limited sensors used and the extra difficulty of both design and control. A joint optimization of the design variables and the controller might be needed for such a difficult task. ■

The traditional approach used for such a kind of task is the sequential method. In the sequential method, design and control are optimized separately, that is, design first then control. Design usually deals with the steady-state performance, such as economic optimality, while control deals with the transient dynamics (Sandoval, Budman, and Douglas, 2008). Thus, the sequential method often causes a poor dynamic performance since it is difficult to obtain an easily controlled process (Georgiadis et al., 2002; Meeuse and Tousain, 2002; Chawankul, 2005).

The integration of design and control can be developed to overcome the weakness of the sequential method, which is an important topic in the process industry. This integration method aims to optimize design and control simultaneously to obtain the desired performance for both design and control (Lewin, 1999; Chawankul, Budman, and Douglas, 2005). The major advantage is that system tasks, including the control task and the design task, can be shared rationally between off-line design and online control, and thus, it could be easier to obtain satisfactory design/control performance. Many integration methods have been studied in the recent decades (Mohideen, Perkins, and Pistikopoulos, 1996, 1997; Bansal et al., 2000a and 2000b; Georgiadis et al., 2002; Chawankul, 2005; Meeuse and Tousain, 2002; Lear, Barton, and Perkins, 1995; Swartz, 2004). However, there is still a long way to go due to the following unsolved problems.

- For easy integration and simplification of the controller design, a simple linear nominal model is usually used to approximate the process. This approximation is effective for a weakly nonlinear process around the operating point. However,

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when the strongly nonlinear process is working in a large operating region, such as Example 1.4, the large approximation error generated will make it difficult to achieve satisfactory performance.

- Little progress is achieved in the design for control, namely to obtain an easily controllable dynamic behavior through process design, before the external control is applied. If control aspects are not considered early in the design process, some complex systems may be rendered difficult to control. A good performance is always a proper balance between design and control aspects.

In general, new integration methods should be developed to overcome the above weaknesses of existing methods.

1.2 OBJECTIVES OF THE BOOK

Based on the analysis of the Section 1.1, the following major objectives are addressed in this book.

1. To develop novel approaches for the robust design of strongly nonlinear systems with large parameter variations and for minimizing the influence of model uncertainty and variations from design variables and model parameters.
2. To consider the dynamic performance, for example, stability and robustness, in system design under model uncertainty and variations from parameters and design variables.
3. To study new methods of integrated design and control, particularly design for control, for the hybrid system, enabling satisfactory performance over a large operating region.
4. To illustrate the application of the presented methods to selected equipment and process in either traditional industry or the modern IC industry.

In support of the above objectives, specific topics discussed in the book include

- a systematic overview and classification on robust analysis/design and the integration of design and control;
- development of robust static design approaches, respectively, for partially unknown systems or nonlinear systems under large parameter variations;
- development of robust dynamic design approaches for both stability and robustness of dynamic processes under parameter variations and model uncertainty;
- development of integrated design and control methods for the hybrid system working in a large operating region.

An attractive feature of this book is that several of the same examples are revisited in different chapters, with variations and enhancements. This will help readers to understand the property of different design methods and approaches.

1.3 CONTRIBUTION AND ORGANIZATION OF THE BOOK

The research fields of this book are depicted in Figure 1.7. The contributions of the book are in three main aspects: robust design for static/dynamic systems and integration of design and control. These actually contribute to the fundamentals of design for advanced manufacturing.

- First, for the static system related to the problems described in Section 1.1.1, three novel robust design approaches will be proposed: the variable sensitivity-based robust design approach for the nonlinear system (Chapter 3), the multi-domain modeling-based robust design for large parameter variation (Chapter 4), and the hybrid model/data-based robust design for both parameter variation and model uncertainty (Chapter 5).
- Second, for the dynamic system related to the problems described in Section 1.1.2, the robust eigenvalue design methods will be developed that allow both stability and robustness of the dynamic system to be maintained under parameter variations (linear system or weakly nonlinear system in Chapter 6, and nonlinear system in Chapter 7) and model uncertainty (Chapter 8).
- Finally, for the integration problem described in Section 1.1.3, two novel methods are proposed for integrating design and control for hybrid systems:
 1. An easily controlled dynamic behavior is first designed under parameter uncertainty, and then integrated with the process control through the robust pole assignment (Chapter 9).
 2. The nonlinear process is modeled with the fuzzy system to work over a large operating region, upon which design and control are integrated for overall performance and optimized with the particle swarm optimization (PSO) method (Chapter 10).

This book presents several newly developed methods for robust design and methods for integrated design and control. The book is organized as shown in Figure 1.8, where topics of chapters and their interconnection are provided for easy understanding. The contents of each chapter will also be summarized below for readers to have a quick knowledge of the whole book.

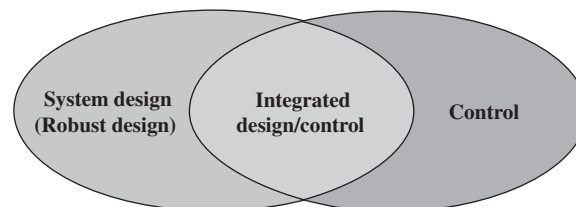


FIGURE 1.7 Research fields covered

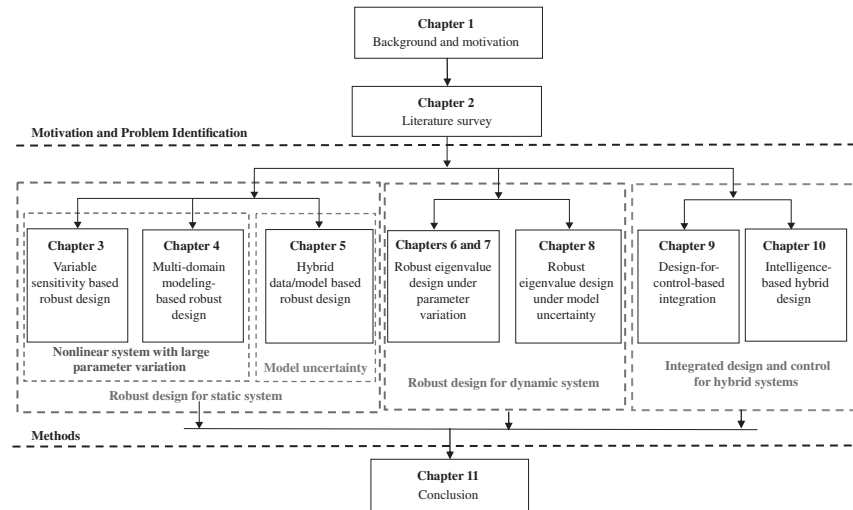


FIGURE 1.8 Organization of the book

In Chapter 2, a systematic overview and classification is presented. The characterization and quantification of uncertainty, robust analysis/design for static and dynamic systems, and the integration of design and control are briefly discussed. Various approaches are reviewed and classified with their limitations and advantages summarized for comparison. This brief overview motivates us to develop new methods for robust design and integrated design/control.

In Chapter 3, variable sensitivity based deterministic and probabilistic robust design approaches are presented for nonlinear systems (Lu, Li, and Chen, 2010; Lu and Li, 2012). A nonlinear system is first formulated using a linear structure. This linear structure will be easy to handle using well-developed robust design methods. A variable sensitivity matrix will be derived for this linear structure when the nonlinearity of the system is considered. Then, the bounds of both the variable sensitivity matrix and its singular values are calculated in a larger design region. Finally, with the variable sensitivity information incorporated, two different robust designs, one of deterministic nature and another of probabilistic nature, are developed to minimize the influence of parameter variation on the original nonlinear system. Since the proposed robust designs consider the influence of the nonlinearity, they can obtain robust performance of the nonlinear system despite uncontrollable variations.

In Chapter 4, a multi-domain modeling-based robust design approach is presented for designing a nonlinear system to be robust under large parameter variations (Lu and Huang, 2013a). Initially, a multi-domain modeling approach is used to model the nonlinear system. The model obtained has a linear structure that is easy to handle using well-developed robust design methods. Then, a robust design method is proposed to minimize the influence of large parameter variations on the performance. Since this approach integrates the merits of both the multi-domain modeling method and the

robust design method to handle the influence of the system nonlinearity as well as large parameter variations, it can effectively ensure robustness of the nonlinear system even if large parameter variations exist.

In Chapter 5, two novel robust design approaches are proposed to improve the system robustness against parameter variations as well as model uncertainty (Lu and Li, 2009b; Lu, Li, and Chen, 2012). The system is first formulated as a linear structure that will be easy to handle by well-developed robust design theories. Its sensitivity matrix incorporates all model uncertainties and nonlinearities. Then, model bounds are estimated from data. Modeling the bound of model uncertainty is easier than modeling the model uncertainty itself. On this basis, the two model-based robust design methods, one deterministic and the other probabilistic, can be easily developed to minimize the influence of parameter variations on performance.

In Chapter 6, two novel robust eigenvalue design approaches are proposed to design the system to be stable and robust under parameter variations (Lu and Li, 2009a). When a linear or weakly nonlinear system has small parameter variations, a linearization model can effectively approximate the system. In this case, stability theory is first applied to obtain a set of design variables and their variation bounds. The system will be stable when design variables stay within these bounds. Then, the robust eigenvalue design is developed to make the dynamic response less sensitive to variations. Furthermore, the tolerance space of the obtained robust design will be maximized to meet the specified performance requirement for dynamic response. When the system has large parameter variations, a multi-model approach is initially developed to formulate the nonlinear relation between dynamic performance and model parameters. A stability design is then developed to guarantee the stability of the dynamic system under large uncontrollable variations. Moreover, a robust design is proposed to achieve the dynamic robustness. Finally, several examples will demonstrate and confirm the effectiveness of the proposed methods.

In Chapter 7, a novel sector nonlinearity (SN) based robust design approach is proposed to design a nonlinear system to be stable and robust. A system can be strongly nonlinear for large parameter variations, and thus difficult for traditional methods to handle. The SN method is first employed to model a nonlinear system. A stability design is then developed to ensure the nonlinear system's stability in a desirable domain under variations. Furthermore, dynamic robustness will be achieved by minimizing the sensitivity of the system eigenvalues to parameter variations. This two-loop optimization method could ensure a nonlinear dynamic system has stability and dynamic robustness under large uncontrollable parameter variation.

In Chapter 8, a novel robust design approach is proposed for stability and robustness of the nonlinear system under model uncertainty (Lu and Li, 2011). First, stability theory and perturbation theory are used to guarantee system stability under model uncertainty. Then, a new robust design is developed to make the dynamic response less sensitive to model uncertainty using matrix perturbation theory. Finally, the tolerance space of the designed variables can be maximized when there are model uncertainties and performance constraints. Thus, the proposed robust design can design the system to have the desired stability and robustness under model uncertainty and variations of design variables.

18 INTRODUCTION

In Chapter 9, a novel method is proposed for integrated design/control of a nonlinear system with hybrid discrete/continuous variables. The controller design is simplified under the robust pole placement (Lu and Huang, 2013b). The key idea in this method is to obtain an easily controlled dynamic behavior through process design, and then integrate the merits of both design and control to ensure robust pole placement under parameter uncertainty. First, a design-for-control approach is developed to make the system controllable and have a good linear approximation. This can effectively reduce the system nonlinearity so that the system designed is easy to control. Then, a novel approach for integrated robust design and control is proposed to guarantee the stability as well as robust pole placement, which can effectively ensure satisfactory dynamic performance under parameter uncertainty.

In Chapter 10, a novel integration of design and control is proposed for the manufacturing system to work in a large operating region with the unmeasured ultimate performance (Lu, Li, Duan, and Sun, 2010; Lu, Li, and Yuan, 2010). The fuzzy modeling method is first employed to approximate the process, upon which fuzzy control rules are developed to achieve stability and robustness. Then, the process design and the control system design are integrated into a unified objective function to consider the global economic performance (high level) as well as the local dynamic performance (low level). Finally, a PSO-based global optimization method is developed to find the solution of this complex integration problem.

Chapter 11 provides conclusions and future challenges.