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Spatio-Temporal Modeling of Nonlinear Distributed Parameter Systems

A Time/Space Separation Based Approach

Springer

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Preface

Distributed parameter systems (DPS) widely exist in many industrial processes, e.g., thermal process, fluid process and transport-reaction process. These processes are described in partial differential equations (PDE), and possess complex spatio-temporal coupled, infinite-dimensional and nonlinear dynamics. Modeling of DPS is essential for process control, prediction and analysis. Due to its infinite-dimensionality, the model of PDE can not be directly used for implementations. In fact, the approximate models in finite-dimension are often required for applications. When the PDEs are known, the modeling actually becomes a *model reduction* problem. However, there are often some unknown uncertainties (e.g., unknown parameters, nonlinearity and model structures) due to incomplete process knowledge. Thus the *data-based modeling* (i.e. *system identification*) is necessary to estimate the models from the process data. The model identification of DPS is an important area in the field of system identification. However, compared with traditional lumped parameter systems (LPS), the system identification of DPS is more complicated and difficult. In the last few decades, there are many studies on the system identification of DPS. The purpose of this book is to provide a brief review of the previous work on model reduction and identification of DPS, and develop new spatio-temporal models and their relevant identification approaches. All these work will be presented in a unified view from time/space separation. The book also illustrates their applications to thermal processes in the electronics packaging and chemical industry.

In the book, a systematic overview and classification on the modeling of DPS is presented first, which includes model reduction, parameter estimation and system identification. Next, a class of block-oriented nonlinear systems in traditional LPS is extended to DPS, which results in the spatio-temporal Wiener and Hammerstein systems and their identification methods. Then, the traditional Volterra model is extended to DPS, which results in the spatio-temporal Volterra model and its identification algorithm. All these methods are based on linear time/space separation. Sometimes, the nonlinear time/space separation can play a better role in modeling of very complex process. Thus, a nonlinear time/space separation based neural modeling is also presented for a class of DPS with more complicated dynamics. Finally, all these modeling approaches are successfully applied to industrial thermal processes, including a catalytic rod, a packed-bed reactor and a snap curing oven.

The book assumes a basic knowledge about distributed parameter systems, system modeling and identification. It is intended for researchers, graduate students and engineers interested in distributed parameter systems, nonlinear systems, and process modeling and control.

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Abbreviations

AE	Algebraic Equation
AIM	Approximated Inertial Manifold
BF	Basis Function
DE	Difference Equation
DPS	Distributed Parameter System
EEF	Empirical Eigenfunction
EF	Eigenfunction
ERR	Error Reduction Ratio
FDM	Finite Difference Method
FEM	Finite Element Method
FMNS	Fading Memory Nonlinear System
IC	Integrated Circuit
IM	Inertial Manifold
IV	Instrumental Variables Method
KL	Karhunen-Loève Decomposition
KL-Hammerstein	Karhunen-Loève based Hammerstein Model
KL-Wiener	Karhunen-Loève based Wiener Model
LDS	Lattice Dynamical System
LPS	Lumped Parameter System
LSE	Least-Squares Estimation
LTI	Linear Time Invariant
MARE	Mean of Absolute Relative Error
MIMO	Multi-Input-Multi-Output
MO	Multi-Output
MOL	Method of Lines

NARX	Nonlinear Autoregressive with Exogenous Input
NL-PCA	Nonlinear PCA
NL-PCA-RBF	NL-PCA based RBF model
ODE	Ordinary Differential Equation
OFR	Orthogonal Forward Regression
PCA	Principal Component Analysis
PCA-RBF	PCA based RBF model
PDE	Partial Differential Equation
POD	Proper Orthogonal Decomposition
RBF	Radial Basis Function
RMSE	Root of Mean Squared Error
SISO	Single-Input-Single-Output
SNAE	Spatial Normalized Absolute Error
SNR	Signal-to-Noise Ratio
SO	Single-Output
SP-Hammerstein	Spline Functions based Hammerstein Model
SP-Wiener	Spline Functions based Wiener Model
SVD	Singular Value Decomposition
TNAE	Temporal Normalized Absolute Error
WRM	Weighted Residual Method

1 Introduction

Abstract. This chapter is an introduction of the book. Starting from typical examples of distributed parameter systems (DPS) encountered in the real-world, it briefly introduces the background and the motivation of the research, and finally the contributions and organization of the book.

1.1 Background

Advanced technological needs, such as, semiconductor manufacturing, nanotechnology, biotechnology, material engineering and chemical engineering, have motivated control of material microstructure, fluid flows, spatial profiles (e.g., temperature field) and product size distributions (Christofides, 2001a). These physical, chemical or biological processes all lead to so called distributed parameter systems (DPS) because their inputs and outputs vary both temporally and spatially. As the significant progress in the sensor, actuator and computing technology, the studies of distributed parameter processes become more and more active and practical in science and engineering. Recently several special issues for control of DPS have been organized by Dochain *et al.* (2003), Christofides (2002, 2004), Christofides & Armaou (2005), and Christofides & Wang (2008). Modeling is the first step for many applications such as prediction, control and optimization. This book will focus on the modeling problem of nonlinear DPS with application examples chosen as industrial thermal processes. In general, the modeling approaches presented are applicable to a wide range of distributed parameter processes.

Next, we will introduce some typical thermal process in integrated circuit (IC) packaging and chemical industry, which will be used as examples in the rest of chapters.

1.1.1 Examples of Distributed Parameter Processes

a) Thermal Process in IC Packaging Industry

One important thermal process in the semiconductor back-end packaging industry considered in this book is the curing process (Deng, Li & Chen, 2005). After the required amount of epoxy is dispensed on the leadframe from the dispenser, and a die is moved from the wafer to attach on the leadframe by the bond arm, then the bonded leadframe is moved into the snap curing oven to cure at a specified temperature. As shown in Figure 1.1, the snap curing oven is an important equipment to provide the required curing temperature distribution. The oven has four heaters for heating and four thermocouples for temperature sensing in the operation. The parts to be cured will be moved in and out from inlet and outlet, respectively.

H.-X. Li and C. Qi: Spatio-Temporal Modeling of Nonlinear DPS, ISCA 50, pp. 1–12.
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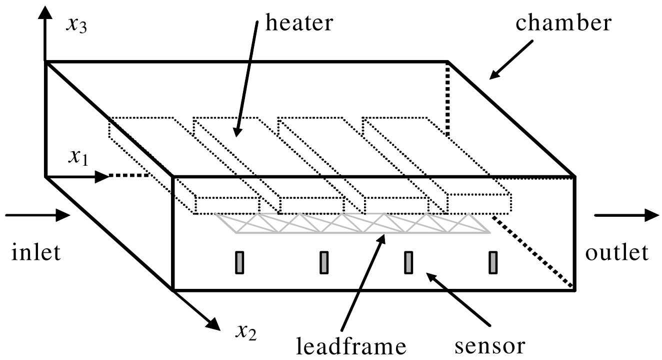

Fig. 1.1 Snap curing oven system

The temperature distribution inside the chamber is often needed for a quality curing control as well as the fundamental analysis for oven design. In practice, it is difficult to place many sensors to measure the temperature distribution during the curing. Thus it motivates us to build a model of the oven and use it to estimate the temperature distribution of the curing process.

This thermal process can be simplified for the easy modeling. The volume of the epoxy between a die and the leadframe is much smaller as compared to the volume of the leadframe and the volume of the oven chamber. Also, the volume of the leadframe is much smaller as compared to the volume of the oven chamber. Thus, the effects of the epoxy and the leadframe on the temperature in the oven chamber are usually neglected in modeling of the curing process. These effects can be considered as disturbances and could be compensated in the later control process.

This thermal process will follow the basic principles of the heat transfer (conduction, radiation and convection). The fundamental heat transfer equation of the oven can be expressed as a nonlinear parabolic partial differential equation (PDE) with some unknown parameters, unknown nonlinearities and unknown boundary conditions:

$$\rho(T)c\frac{\partial T}{\partial t} = \frac{\partial}{\partial x_1}\left(k(T)\frac{\partial T}{\partial x_1}\right) + \frac{\partial}{\partial x_2}\left(k(T)\frac{\partial T}{\partial x_2}\right) + \frac{\partial}{\partial x_3}\left(k(T)\frac{\partial T}{\partial x_3}\right) + f_c(T) + f_r(T) + bu(t), \tag{1.1}$$

where

$T = T(x_1, x_2, x_3, t)$ is the temperature at time t and location (x_1, x_2, x_3),

$x_1 \in [0, x_{10}]$, $x_2 \in [0, x_{20}]$ and $x_3 \in [0, x_{30}]$ are spatial coordinates,

$k(T)$ is the thermal conductivity, which is usually inaccurately given,

$\rho(T)$ is the density, which is usually inaccurately given,

c is the specific heat,