

Studies in Systems, Decision and Control 178

Qinyuan Liu  
Zidong Wang  
Xiao He

# Stochastic Control and Filtering over Constrained Communication Networks

 Springer

# **Studies in Systems, Decision and Control**

Volume 178

## **Series editor**

Janusz Kacprzyk, Polish Academy of Sciences, Warsaw, Poland  
e-mail: [kacprzyk@ibspan.waw.pl](mailto:kacprzyk@ibspan.waw.pl)

The series “Studies in Systems, Decision and Control” (SSDC) covers both new developments and advances, as well as the state of the art, in the various areas of broadly perceived systems, decision making and control—quickly, up to date and with a high quality. The intent is to cover the theory, applications, and perspectives on the state of the art and future developments relevant to systems, decision making, control, complex processes and related areas, as embedded in the fields of engineering, computer science, physics, economics, social and life sciences, as well as the paradigms and methodologies behind them. The series contains monographs, textbooks, lecture notes and edited volumes in systems, decision making and control spanning the areas of Cyber-Physical Systems, Autonomous Systems, Sensor Networks, Control Systems, Energy Systems, Automotive Systems, Biological Systems, Vehicular Networking and Connected Vehicles, Aerospace Systems, Automation, Manufacturing, Smart Grids, Nonlinear Systems, Power Systems, Robotics, Social Systems, Economic Systems and other. Of particular value to both the contributors and the readership are the short publication timeframe and the world-wide distribution and exposure which enable both a wide and rapid dissemination of research output.

More information about this series at <http://www.springer.com/series/13304>

Qinyuan Liu · Zidong Wang  
Xiao He

# Stochastic Control and Filtering over Constrained Communication Networks

 Springer

Qinyuan Liu  
Department of Computer Science  
and Technology  
Tongji University  
Shanghai, China

Xiao He  
Department of Automation  
Tsinghua University  
Beijing, China

Zidong Wang  
Department of Computer Science  
Brunel University London  
Uxbridge, UK

ISSN 2198-4182                      ISSN 2198-4190 (electronic)  
Studies in Systems, Decision and Control  
ISBN 978-3-030-00156-8              ISBN 978-3-030-00157-5 (eBook)  
<https://doi.org/10.1007/978-3-030-00157-5>

Library of Congress Control Number: 2018953301

MATLAB<sup>®</sup> is a registered trademark of The MathWorks, Inc., 1 Apple Hill Drive, Natick, MA 01760-2098, USA, <http://www.mathworks.com>.

© Springer Nature Switzerland AG 2019

This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, express or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Switzerland AG  
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

# Preface

Network control systems (NCSs) are spatially distributed systems whose components, such as actuators, sensors, and controllers, are connected via a shared communication network. Due to the advantages of flexible architectures, reduced installation and maintenance cost, and high reliability, NCSs have attracted increasing attention from researchers and have been widely applied in a broad range of fields such as unmanned aerial vehicles, intelligent building, remote surgery, and automated highway systems. However, it should be stressed that the communication networks in practice are usually resource-constrained, and therefore, some network-induced phenomena would inevitably emerge during the signal transmission, which include, but are not limited to, communication rate constraints, signal-to-noise constraints, channel fading, communication delays, packet dropout, signal quantization, and so on. These phenomena have a great impact on the signals transmitted through communication networks making executors (or estimators) unaware of the exact signals from controller (or sensor). In this case, the performance of NCSs can no longer be guaranteed when utilizing the traditional estimation/filtering techniques. Consequently, it is of practical significance to establish new techniques for control and filtering of the networked system under constrained communication networks. Generally speaking, the research on this topic is concerned with the interplay between three realms: control theory, communication theory, and information theory. The main challenge lies in the signal distortions and the information constraints in the communication loop due to imperfect network conditions.

The objective of this book is to present the up-to-date research developments and novel methodologies on stochastic control and filtering for networked systems under constrained communication networks. The content of this book can be divided into two parts, where the first part (Chaps. 2 and 3) presents control design methodologies and the second part (Chaps. 4–11) shows the filter design methodologies. This work provides a framework of optimal controller/filter design, resilience operation, stability analysis, and performance analysis for the considered systems subject to various kinds of communication constraints such as signal-to-noise constraints, bandwidth constraints, packet drops, etc. Several

techniques including recursive Riccati equations, matrix decomposition, optimal estimation theory, and mathematical optimization methods are employed to develop the controller/filters with specific performance. In addition, this book provides valuable reference materials for researchers who wish to explore the area of control and filtering under constrained communication networks.

The compendious frame and description of the book are given as follows. Chapter 1 introduces the recent advances on stochastic control and filtering problems for networked systems and the outline of the book. Chapter 2 is concerned with the state feedback stabilization for NCSs subject to signal-to-noise constrained fading channels. Chapter 3 studies the  $H_\infty$  consensus control of multi-agent systems, where an event-based mechanism is introduced to reduce the consumption of network resources. Chapter 4 considers the event-based filter design problem for a class of discrete-time stochastic systems. The resilience issue is taken into account in order to accommodate the possible gain variations in the course of filter implementation. Chapter 5 deals with the event-based distributed filtering over wireless sensor networks with bandwidth and energy constraints, and establishes the sufficient conditions for the convergence of the filtering error systems. Chapter 6 extends the results in Chap. 5 to the wireless sensor networks with Markovian switching topologies. Chapter 7 addresses the minimum-variance recursive distributed filter design problems under event-based communication strategies, based on which Chap. 8 further considers the resilience and stability issues. In Chap. 9, a consensus-based distributed filter is developed for a class of discrete time-varying systems subject to stochastic nonlinearities. Chapter 10 discusses the convergence issues for consensus-based distributed filter subject to random link failures. Chapter 11 is concerned with the moving-horizon state estimation problems for a class of discrete-time complex networks under binary encoding schemes. Chapter 12 gives the conclusion and some possible future research topics. Simulations presented in this book are implemented using The MathWorks, Inc. MATLAB software package.

This book is a research monograph whose intended audience is graduate and postgraduate students as well as researchers. The background required of the reader is knowledge of basic stochastic process, basic control system theory, basic Lyapunov stability theory, and basic optimal estimation theory.

Shanghai, China  
Uxbridge, UK  
Beijing, China  
January 2018

Qinyuan Liu  
Zidong Wang  
Xiao He

# Acknowledgements

This book would not have been possible without the help, support, and guidance of many people. The authors would like to express their deep appreciation to those who have been directly involved in various aspects of the research leading to this book.

Special thanks go to Professor Donghua Zhou from Tsinghua University, and Professor Li Qiu and Research Assistant Professor Wei Chen from the Hong Kong University of Science and Technology for their valuable suggestions, constructive comments, and support. The authors also extend our thanks to many colleagues who have offered support and encouragement throughout this research effort. In particular, we would like to acknowledge the contributions from Bo Shen, Guoliang Wei, Hongli Dong, Lifeng Ma, Derui Ding, Jun Hu, Liang Hu, Jinling Liang, Yang Liu, Yurong Liu, Nianyin Zeng, Sunjie Zhang, and Lei Zou. Last but not the least, the authors are especially grateful to their families for their encouragement and never-ending support when it was most required.

The writing of this book was supported in part by the National Natural Science Foundation of China under Grants 61490701, 61525305, 61473163, 61522309, 61873148, 61803282, and 61733009, the Royal Society of the UK, the Research Fund for the Taishan Scholar Project of Shandong Province of China, and the Alexander von Humboldt Foundation of Germany. The work of Xiao He was also partially supported by the R&D Project of Intelligent Ship 1.0 from China's Ministry of Industry and Information Technology under Grant [2016]544, the Special Fund of Suzhou-Tsinghua Innovation Leading Action under Grant 2016SZ0202, and the National Key Research and Development Program of China under Grant 2017YFA0700300. The support of these organizations is gratefully acknowledged. The third author also expresses his acknowledgement for the support from Beijing Association of Automation.

Shanghai, China  
Uxbridge, UK  
Beijing, China  
January 2018

Qinyuan Liu  
Zidong Wang  
Xiao He

# Contents

<b>1</b>	<b>Introduction</b> . . . . .	1
1.1	Concepts and Challenges in Networked Control Systems . . . . .	1
1.1.1	Networked Control Systems . . . . .	1
1.1.2	Constrained Communication Networks . . . . .	2
1.2	Analysis and Synthesis of Networked Control Systems . . . . .	4
1.2.1	Signal Quantization . . . . .	4
1.2.2	Communication Delay . . . . .	6
1.2.3	Packet Dropout . . . . .	7
1.2.4	SNR Constraints . . . . .	9
1.3	Event-Based Control and Filtering Problems . . . . .	9
1.3.1	Event-Based Control for Networked Control Systems . . . . .	10
1.3.2	Event-Based Consensus Control for Multi-agent Systems . . . . .	11
1.3.3	Event-Based Remote State Estimation . . . . .	13
1.4	Outline of This Book . . . . .	15
	References . . . . .	17
<b>2</b>	<b>Feedback Stabilization of Networked Systems over Fading Channels</b> . . . . .	23
2.1	Problem Formulation . . . . .	24
2.2	Preliminary . . . . .	27
2.2.1	Mean-Square Stability . . . . .	27
2.2.2	Wonham Decomposition . . . . .	27
2.2.3	Optimal Complementary Sensitivity . . . . .	28
2.3	Main Results . . . . .	29
2.4	An Illustrative Example . . . . .	32
2.5	Conclusions . . . . .	34
	References . . . . .	34

<b>3</b>	<b>Event-Based <math>H_\infty</math> Consensus Control of Multi-agent Systems</b>	37
3.1	Problem Formulation	39
3.1.1	Graph Topologies	39
3.1.2	Multi-agent Systems	40
3.1.3	Cooperative Estimators Design	41
3.1.4	Event-Based Mechanism	41
3.2	Main Results	44
3.3	An Illustrative Example	51
3.4	Conclusions	54
	References	54
<b>4</b>	<b>Event-Triggered Resilient Filtering with Measurement Quantization</b>	57
4.1	Problem Formulation	58
4.2	Main Results	62
4.3	Performance Analysis	68
4.3.1	Monotonicity	68
4.3.2	A Steady-State Filter	69
4.4	An Illustrative Example	72
4.5	Conclusions	74
	References	75
<b>5</b>	<b>Event-Based Distributed Filtering of Continuous-Time Nonlinear Systems</b>	77
5.1	Problem Formulation and Preliminaries	79
5.1.1	Wireless Sensor Networks	79
5.1.2	Event-Based Distributed Filtering Strategies	81
5.2	Main Results	84
5.2.1	Stability Analysis and Filter Design	84
5.2.2	Adaptive Thresholds	90
5.3	An Illustrative Example	91
5.3.1	Comparison with Consensus-Based Distributed Filters	95
5.4	Conclusions	96
	References	97
<b>6</b>	<b>Event-Based Distributed Filtering over Markovian Switching Topologies</b>	99
6.1	Problem Formulation	100
6.1.1	Markovian Switching Topologies	100
6.1.2	Wireless Sensor Networks	101
6.1.3	Event-Based Distributed Filter	102
6.2	Main Results	104

- 6.3 An Illustrative Example . . . . . 112
- 6.4 Conclusions . . . . . 114
- References . . . . . 114
- 7 Event-Based Recursive Distributed Filtering . . . . . 117**
  - 7.1 Problem Formulation and Preliminaries . . . . . 119
    - 7.1.1 Traditional Distributed Filter Structure . . . . . 119
    - 7.1.2 Event-Based Distributed Filter Structure . . . . . 120
  - 7.2 Main Results . . . . . 122
  - 7.3 An Illustrative Example . . . . . 129
  - 7.4 Conclusions . . . . . 132
  - References . . . . . 133
- 8 A Resilient Approach to Distributed Recursive Filter Design . . . . . 135**
  - 8.1 Problem Formulation . . . . . 137
    - 8.1.1 Target Plant and Sensor Network . . . . . 137
    - 8.1.2 Distributed Resilient Filter . . . . . 138
  - 8.2 Preliminary . . . . . 140
  - 8.3 Suboptimal Distributed Resilient Filter Design . . . . . 143
  - 8.4 Boundedness Analysis . . . . . 148
  - 8.5 An Illustrative Example . . . . . 151
  - 8.6 Conclusions . . . . . 156
  - References . . . . . 156
- 9 Consensus-Based Recursive Distributed Filtering . . . . . 159**
  - 9.1 Problem Formulation and Preliminaries . . . . . 160
    - 9.1.1 Target Plant and Sensor Network . . . . . 160
    - 9.1.2 Consensus-Based Filtering Algorithm . . . . . 162
  - 9.2 Main Results . . . . . 164
  - 9.3 An Illustrative Example . . . . . 168
  - 9.4 Conclusions . . . . . 172
  - References . . . . . 172
- 10 On Kalman-Consensus Filtering with Random Link Failures . . . . . 173**
  - 10.1 Problem Formulation . . . . . 175
    - 10.1.1 Topology Structure . . . . . 175
    - 10.1.2 Target Plant and Measurement Models . . . . . 175
    - 10.1.3 Kalman-Consensus Filtering . . . . . 176
  - 10.2 Preliminary for Boundedness Analysis . . . . . 178
  - 10.3 Boundedness Analysis . . . . . 180
    - 10.3.1 Finite Number of Consensus Steps . . . . . 181
    - 10.3.2 Infinite Number of Consensus Steps . . . . . 187
  - 10.4 Simulation Example . . . . . 189
  - 10.5 Conclusions . . . . . 192
  - References . . . . . 193

- 11 Moving-Horizon Estimation with Binary Encoding Schemes . . . . . 195**
  - 11.1 System Description . . . . . 197
    - 11.1.1 Complex Networks . . . . . 197
    - 11.1.2 Binary Encoding Schemes . . . . . 197
  - 11.2 Preliminary . . . . . 199
  - 11.3 Centralized Moving-Horizon Estimation . . . . . 202
  - 11.4 Decentralized Moving-Horizon Estimation . . . . . 208
  - 11.5 An Illustrative Example . . . . . 215
  - 11.6 Conclusions . . . . . 219
  - References . . . . . 219
  
- 12 Conclusion and Further Work . . . . . 221**

# Abbreviations

$\odot$	The Hadamard product
$\otimes$	The Kronecker product
$\mathbb{R}^n$	The $n$ -dimensional Euclidean space
$\mathbb{R}^{n \times m}$	The set of all $n \times m$ real matrices
$\mathbb{R}^+$	The set of all positive real numbers
$\mathbb{N}$	The set of natural numbers
$\mathbb{S}_+^n$	The set of $n \times n$ positive-definite matrices
$A^T$ or $A'$	The transpose of matrix $A$
$A^\dagger$	The Moore–Penrose pseudoinverse of matrix $A$
$A > 0$	The matrix $A$ is positive definite
$A \geq 0$	The matrix $A$ is positive semidefinite
$A < 0$	The matrix $A$ is negative definite
$A \leq 0$	The matrix $A$ is negative semidefinite
$\  \cdot \ $	The Euclidian norm of real vectors or the spectral norm of real matrices
$\  x \ _M^2$	The quadratic form $x'Mx$
$\  A \ _{min}$	The smallest singular value of matrix $A$
$\lambda_{max}(A)$	The eigenvalue of matrix $A$ with the largest modulus
$\lambda_2(A)$	The eigenvalue of matrix $A$ with the second largest modulus
$\text{tr}(A)$	The trace of matrix $A$
$\mathbb{P}\{\cdot\}$	The occurrence probability of the event “.”
$\mathbb{E}\{x\}$	The expectation of stochastic variable $x$
$\text{Var}\{x\}$	The variance of stochastic variable $x$
$\mathbb{E}\{x y\}$	The conditional expectation of $x$ given $y$
$I$	The identity matrix of compatible dimension
$\mathbf{0}_n$	The $n \times n$ zero matrix
$\mathbf{1}_n$	The $n \times 1$ column vector with all elements equal to 1
$\text{vec}\{x_1, x_2\}$	The column vector $[x_1^T, x_2^T]^T$
$\text{vec}_n\{x_i\}$	The column vector $\text{vec}\{x_1^T, x_2^T, \dots, x_n^T\}$

$\text{diag}\{x_1, x_2\}$	The block diagonal matrix with $i$ th block being $x_i$ and all other entries being zero
$\text{diag}_n\{A_i\}$	The block diagonal matrix $\text{diag}\{A_1, A_2, \dots, A_n\}$
$\{M_{ij}\}_{n \times n}$	The partitioned matrix with $M_{ij}$ being $(i, j)$ -th block submatrix
$\mathcal{L}_2([0, T]; \mathbb{R}^n)$	The space of square-summable $n$ -dimensional vector functions over $[0, T]$

# List of Figures

Fig. 1.1	A typical architecture of NCSs . . . . .	2
Fig. 2.1	Networked control systems . . . . .	25
Fig. 2.2	Auxiliary networked control systems . . . . .	29
Fig. 2.3	Closed-loop evolution of $\ X(t)\ _F$ . . . . .	33
Fig. 3.1	The graph . . . . .	51
Fig. 3.2	The state trajectories $x_i^{(1)}(k)$ . . . . .	52
Fig. 3.3	The state trajectories $x_i^{(2)}(k)$ . . . . .	53
Fig. 3.4	The consensus error $\bar{z}_i(k)$ . . . . .	53
Fig. 3.5	The triggering instants . . . . .	54
Fig. 4.1	The event-triggered instants and the intervals. The x-coordinate of the stems represents the instants when an event occurs and the length of the stems is the interval between two successive events . . . . .	73
Fig. 4.2	Compare the upper bound $\log_{10}(\text{tr}(M_{k+1 k}))$ and the mean-square errors $\log_{10}(\mathbb{E}[e'_{k k}e_{k k}])$ on the condition of different thresholds $\sigma_i$ . . . . .	73
Fig. 4.3	Compare the steady-state bound $\log_{10}(\text{tr}(\mathcal{P}))$ and the mean-square error $\log_{10}(\mathbb{E}[e'_{k+1 k}e_{k+1 k}])$ . . . . .	74
Fig. 5.1	The architecture of the WSN . . . . .	80
Fig. 5.2	Configuration of the event-based distributed filtering system. . . . .	82
Fig. 5.3	The sensor network. . . . .	92
Fig. 5.4	The topology of the directed graph $\mathcal{G}$ . . . . .	92
Fig. 5.5	Mean-square error of EBDF with initial target states $x(0)$ . . . . .	94
Fig. 5.6	The inter-event time for $k = 0, 1, 2, \dots$ . . . . .	94
Fig. 5.7	The adaptive threshold . . . . .	95
Fig. 5.8	EBDF compared with CBDF . . . . .	96

Fig. 6.1 **a** and **b** are the topology of  $\mathcal{G}_1$  and  $\mathcal{G}_2$ , respectively.  
**c** is the topology of the combined graph. . . . . 112

Fig. 6.2 The evolution of the mean-square error . . . . . 113

Fig. 7.1 The state  $x_1$  and its estimation . . . . . 130

Fig. 7.2 The state  $x_2$  and its estimation . . . . . 130

Fig. 7.3 The triggering sequence . . . . . 131

Fig. 7.4 The trace of error covariance and its upper boundary. . . . . 131

Fig. 8.1 The topology of the WSN . . . . . 151

Fig. 8.2 The true state  $x^{(1)}(k)$  and its estimates  $\hat{x}_i^{(1)}(k|k)$  . . . . . 153

Fig. 8.3 The true state  $x^{(2)}(k)$  and its estimates  $\hat{x}_i^{(2)}(k|k)$  . . . . . 154

Fig. 8.4 The estimation error of  $x^{(1)}(k)$  . . . . . 154

Fig. 8.5 The estimation error of  $x^{(2)}(k)$  . . . . . 155

Fig. 8.6 The MSE and its upper bound  $\text{tr}\{M_{k|k}\}$  . . . . . 155

Fig. 8.7 MSE Comparison for the proposed resilient filter  
and the filter in [25] . . . . . 156

Fig. 9.1 The state  $x_1$  and its estimation,  $L = 1$ . . . . . 169

Fig. 9.2 The state  $x_2$  and its estimation,  $L = 1$ . . . . . 170

Fig. 9.3 The state  $x_1$  and its estimation,  $L = 3$ . . . . . 170

Fig. 9.4 The state  $x_2$  and its estimation,  $L = 3$ . . . . . 171

Fig. 9.5 MSE and its upper bound. . . . . 171

Fig. 10.1 A wireless sensor network. Sensor A and Sensor B  
are able to measure the position of the target on the  $x$ -axis  
and  $y$ -axis, respectively. Non-Sensor Node only has  
the communication and signal processing capabilities. . . . . 190

Fig. 10.2 Position ARMSE of the Kalman-consensus filters under  
difference link failure rates. The number of consensus  
steps is chosen as  $L = 1$  . . . . . 191

Fig. 10.3 Position ARMSE of the Kalman-consensus filters under  
difference measurement noise variances. The number of  
consensus steps is chosen as  $L = 1$  . . . . . 191

Fig. 10.4 Variance of the position error  $\text{tr}(\Xi P_k^i)$ ,  $i = 1, \dots, 70$ ,  
where  $\Xi = \text{diag}\{1, 0, 1, 0\}$ . . . . . 192

Fig. 11.1 The binary encoding schemes. . . . . 198

Fig. 11.2 Centralized moving-horizon estimation. . . . . 202

Fig. 11.3 Decentralized moving-horizon estimation . . . . . 208

Fig. 11.4 The topology of the coupled network. . . . . 215

Fig. 11.5 The actual measurements and the distorted measurement  
via quantized BSCs. . . . . 216

Fig. 11.6 The first entry of the plant states and their estimates  
based on the centralized moving-horizon estimation. . . . . 217

Fig. 11.7 The second entry of the plant states and their estimates  
based on the centralized moving-horizon estimation. . . . . 217

Fig. 11.8	The first entry of the plant states and their estimates based on the decentralized moving-horizon estimation . . . . .	218
Fig. 11.9	The second entry of the plant states and their estimates based on the decentralized moving-horizon estimation . . . . .	218

# Chapter 1

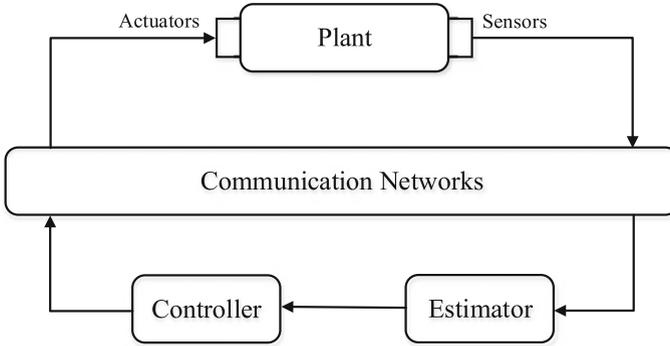
## Introduction



### 1.1 Concepts and Challenges in Networked Control Systems

#### 1.1.1 Networked Control Systems

Networked control systems (NCSs) are spatially distributed systems in which signals between the system components (e.g., sensors, controllers, and actuators) are transmitted via a communication network. Thanks to the rapid development of communication technologies and the increasing demand of remote control, NCSs have gained considerable research interests in the circles of both industry and academia for decades. A typical architecture of NCSs is shown in Fig. 1.1. The sensor devices first convert a physical stimulus of the plant that we are interested in into a readable measurement, and then transmit the measurement to estimators to restore the internal state of the plant. Based on the estimates, the controllers generate the control input and then send it to the actuators to control the plant. That is, the closed-loop control is implemented with the help of communication networks. Using shared communication networks to transfer measurements from sensors to estimators, and control input from controllers to actuators, can greatly ease the complexity of connections, provide more flexibility in architectures, and reduce maintenance costs and troubleshooting. As such, NCSs have found a wide range of applications in engineering practice including mobile sensor networks [1, 2], remote surgery [3, 4], remote diagnostics [5, 6], process control engineering [7, 8], power systems [9, 10], and unmanned aerial vehicles [11, 12].



**Fig. 1.1** A typical architecture of NCSs

### 1.1.2 Constrained Communication Networks

Traditional control theory ignores the influence of communication networks or assumes that the communication networks have sufficient large bandwidth so that the communication and control can be treated as two independent processes. Much research effort has been devoted to the fundamental issues such as stability, optimality, resilience, robustness, and decentralization. However, in the emerging applications, such as mobile sensor networks, the signals are sent through wireless channels whose communication bandwidth is quite limited. As a result, the transmitted signals may be distorted, delayed, lost, and sometimes even not be allowed for transmission. All these problems challenge the validity of the traditional control theory in NCSs. Therefore, the NCSs with constrained communication networks have received increasing attention, and more and more researchers have begun to investigate the impact of communication networks on control theory in recent years. According to the available results in the literature, some specific phenomena induced by constrained networks are listed in the following context and their corresponding mathematical models are shown in Table 1.1.

- **Signal quantization.** In NCSs, data is sent through digital communication networks in the form of packets. Usually, the analog signals must be transformed into digital ones by quantizers before transmission. Due to the bandwidth limits, the quantized signals are with a finite word length, which certainly introduces some degree of information loss in the communication process.
- **Communication delay.** Data exchange among the components connected through communication networks suffers from communication delays, which are composed of the sensor-to-estimator delay and the controller-to-actuator delay. The length of time delays is determined by various factors, including the processing speed of devices, the routing algorithm, the network burden, and so on.
- **Packet dropout.** Packet dropout is typically caused by network congestion. The data packets must travel through multiple devices and links to their destination.

**Table 1.1** Mathematical models of some phenomena induced by constrained networks

Types	Mathematical models
Signal quantization	<p>There are various types of quantizers. Here, we take a uniform quantizer for an example. The set of quantization levels for the quantizer is described by</p> $\mathcal{U} = \{\tau_t   \tau_t \triangleq t\Delta, t = 0, \pm 1, \pm 2, \dots\}, \Delta > 0. \quad (1.1)$ <p>The quantization function <math>Q(\cdot)</math> maps the transmitted signal <math>y \in \mathbb{R}</math> into the set <math>\mathcal{U}</math>. When <math>\tau_t \leq y(k) \leq \tau_{t+1}</math>, the signal <math>Q(y) = \tau_t</math></p>
Communication delay	Denote the transmitted signal and received signal at instant $k$ by $y(k)$ and $\hat{y}(k)$ , respectively, and then the communication delay can be represented by $\hat{y}(k) = y(k - \tau_k)$ with $\tau_k$ being the time delay
Packet dropout	A Bernoulli random variable $\gamma_k$ can be utilized to characterize the packet dropout at instant $k$ . If $\gamma_k = 0$ , the packet dropout occurs, and if $\gamma_k = 1$ , the packet is sent successfully
SNR constraints	<p>The SNR is considered when the distribution of all signals converges to a stationary distribution. In this case, the power of the transmitted signal <math>y</math> and the channel noise are defined by <math>\ y\ _{Pow}</math> and <math>\Phi</math>. Under the SNR constraints, it has</p> $SNR = \frac{\ y\ _{Pow}}{\Phi} \leq \frac{P}{\Phi} \quad (1.2)$ <p>where <math>P</math> is the admissible transmission power level</p>

When the number of data packets in the transmission sequence overalls the maximum load of the network, network congestion happens, which may result in packet dropout.

- **Signal-to-noise ratio constraints.** Signal-to-noise ratio (SNR), which is defined as the ratio of signal power to noise power, is a measure of the signal strength relative to the background noise in the communication process. For a specific communication network, the data transfer is subject to certain SNR constraints due to the transmission power limits.
- **Bandwidth and energy constraints.** Limited by the capacity of network devices, the bandwidth of communication networks and the energy of transistors are usually restricted.

Generally speaking, the research on NCSs is concerned with the interplay between three realms: control theory, communication theory, and information theory. The main challenge lies in the signal distortions and the information constraints in the communication loop due to imperfect network conditions.

## 1.2 Analysis and Synthesis of Networked Control Systems

In this chapter, the research on analysis and synthesis of NCSs under four different network-induced effects, i.e., signal quantization, communication delay, packet dropout, and SNR constraints, will be reviewed.

### 1.2.1 Signal Quantization

As signal quantization is impossible to be performed with infinite precision, it inevitably leads to quantization errors acting on the transmitted signals. Therefore, it is of practical importance to carry out analysis on the quantizers and investigate whether the quantized control/filtering systems can achieve the desired performance. The studies of the signal quantization date back to 1956, when Kalman pointed out that, under quantization schemes, the controlled output might present complicated behaviors such as limit circles and chaos [13]. Since then, the quantized networked systems have gained more and more research attention, and many results have been presented in the literature. Generally speaking, quantizers can be classified into two categories, that is, static quantizer and dynamic quantizer. A static quantizer, in fact, is a memoryless nonlinear function mapping the signals into a quantization set. According to the types of nonlinear functions, the static quantizer can be further classified into several categories including the uniform quantizer, the probabilistic uniform quantizer, the logarithmic quantizer, etc.

As can be seen in (1.1), the quantization levels of a uniform quantizer are equal, and, therefore, the corresponding quantization error affecting the received data can be described as an additive noise with bounded norm. In [14], the tracking problems of an uncertain LTI system with uniformly quantized control input have been studied. A study of visual tracking control of a wheeled mobile robot subject to velocity quantization uncertainties has been presented in [15], where a robust control law that overcomes the unmodeled quantization effect is established. The authors in [16] have considered the cooperative control under uniformly quantized information for multi-agent systems, and have shown that the dynamics of agents will enter a ball when there is a tree in the communication topology.

It should be stressed that, with the uniform quantizer, the asymptotic behaviors of the NCSs cannot be guaranteed [17, 18], so a probabilistic uniform quantizer has been introduced to deal with such an issue. The probabilistic uniform quantizer has the same quantization set as the uniform quantizer, while the major difference lies in that the quantizer function of the former is a stochastic one. To be specific, in a probabilistic uniform quantizer, the quantizer output can be defined as follows:

$$\begin{cases} \mathbb{P}\{Q(y) = \tau_t\} = 1 - r \\ \mathbb{P}\{Q(y) = \tau_{t+1}\} = r, \end{cases} \quad (1.3)$$

where  $r = \frac{y-\tau_t}{\delta} \in [0, 1]$ . In this case, the quantization error, defined by  $e = y - Q(y)$ , is an additive random variable with zero mean and bounded variance. In [19], a consensus protocol has been proposed in which the agents employ probabilistically quantized information to communicate with the neighboring nodes; it has been proved that consensus can be achieved with the expected consensus value equal to the average of the initial values of agents. Furthermore, a mean-squared error convergence analysis of the consensus error has been proved as time goes to infinity in [20].

The (probabilistic) uniform quantizer uniformly divides the whole segment into equal quantization levels. As compared to the uniform quantizer, the relation between two quantization levels in the logarithmic quantizer is logarithmic. It has been shown in [21] that the logarithmic quantizer is the coarsest quantizer that can quadratically stabilize a single-input linear discrete-time invariant system, and hence the logarithmic quantizer is more preferable in NCSs since it greatly reduces the transmitted bits. In a typical logarithmic quantizer, the set of quantization levels is described by

$$\mathcal{U} = \{\pm\tau_t | \tau_t \triangleq \rho^t \tau_0, t = 0, \pm 1, \pm 2, \dots\} \cup \{0\} \cup \{\pm\tau_0\}, \quad (1.4)$$

where  $0 < \rho < 1$ ,  $\tau_0 > 0$ . The quantized function  $Q(\cdot)$  is usually symmetric, i.e.,  $Q(y) = -Q(-y)$ , with the following form:

$$Q(y) = \begin{cases} \tau_t, & \frac{1}{1+\delta}\tau_t \leq y \leq \frac{1}{1-\delta}\tau_t \\ 0, & y = 0 \\ -Q(-y), & y < 0 \end{cases} \quad (1.5)$$

where  $\delta = (1-\rho)/(1+\rho)$ . According to the results in [22], the logarithmic quantization effects can be described by sector bound uncertainties, that is,  $Q(y) = (1+\Delta)y$  for uncertainties  $\Delta$  satisfying  $\|\Delta\| \leq \delta$ . The robust analysis methods can be applied to study the stability of quantized control/filtering problems, see, e.g., [23–25] and the references therein. For instance, in [23], Fu and Souza have considered the state estimation problem for networked systems with quantized measurements. The results have revealed the relationship between quantization density and the asymptotic convergence of estimation error variance. The quantized feedback control problem has been considered in [25], where the authors have utilized a quantization dependent Lyapunov function to establish a sufficient condition for stabilization in terms of linear matrix inequalities (LMIs).

The dynamic quantizer can automatically adjust the quantization policy based on the current and the historical data, and thus is more complicated but effective than the static one. A distinct advantage of the dynamic quantizer is that it can stabilize the networked system by using a finite number of quantization levels [26, 27]. In [27, 28], a novel quantized control approach has been proposed, which allows the change of quantizer sensitivity when the system evolves. In this setup, the dynamic quantizer scheme can be divided into two stages: zoom-out stage and zoom-in stage. At the zoom-out stage, the quantization level is increased until the quantizer input

can be adequately measured, and subsequently, at zoom-in stage, the quantization level is decreased to drive the state of the plant to zero. Another type of dynamic quantizers is based on the dynamic scaling of quantizer input. That is, the input signal is pre-scaled by the quantizer to make its range be suitable for quantization [26].

### 1.2.2 Communication Delay

Since the bandwidth of networks and the capacity of transmission devices are both limited, time delays are inevitable in the communication process. The length of communication delays is usually determined by various factors, such as the processing speed of devices, the routing algorithm, and the network burden. In many situations, communication delay is a source of instability [29], and hence it is of theoretical and practical importance to take the communication delays into consideration in the analysis and synthesis of the NCSs. According to the available results in the literature, the communication delays can be described by two models: constant delay and time-varying delay.

The constant delay is the simplest model of the communication delay, but it indeed can be utilized to describe a class of practical applications, wherein the buffers in the receiver is longer than the worst-case delay time [30]. A drawback of such a treatment is its conservatism as the signal delay becomes longer than its actual transfer delay. The analysis and synthesis issues of the NCSs with constant delay have been studied in [31], where the authors give the stability region of the closed-loop systems. For consensus issues of multi-agent systems with constant communication delay, a sufficient condition for consensus has been presented in the form of linear matrix inequalities in [32]. Further studies in [33] have pointed out that for first-order multi-agent systems, the constant communication delay does not affect the consensusability.

Because of stochastic and time-varying properties of network environment, the constant delay is insufficient to characterize the practical communication delay in reality. Recently, significant research effort has been devoted to the analysis and synthesis of networked systems with time-varying delays, which can be modeled in various ways according to the prior knowledge of the communication delay. A simplest way to describe time-varying delays is treating them as an uncertainty with given lower and upper bounds, e.g., the communication delay  $\tau_k$  satisfies

$$\underline{\tau} \leq \tau_k \leq \bar{\tau}, \quad \text{for } \underline{\tau}, \bar{\tau} \geq 0.$$

In [34], Yue et al. have established the sufficient condition for the asymptotic stability of NCSs with bounded delay by using an linear matrix inequality approach. In [35], the remote state estimation for networked systems with bounded delays have been investigated. The exponential synchronization for complex networks with bounded communication delays has been discussed in [36].

Another way to describe time-varying delays is treating them as random variables. For example, in [37], the delays have been assumed to be a random variable with known statistical properties, and the “probabilistic delay averaging” approach has been utilized to deal with the optimal control issues. In [38], Nilsson et al. have considered that the time delays are independent and their probability distributions are known a priori. An optimal stochastic control scheme has been proposed when the timestamps of the delays are available. In [39], a binary delay has been employed to describe the random communication delay by using a Bernoulli-distributed white sequence, and an  $H_\infty$  control method has been established for both the exponential stability and the  $H_\infty$  performance of the networked system.

It is worth noticing that, in the aforementioned random delays, the communication delays are assumed to be statistically independent from transfer to transfer. This assumption, however, is quite restrictive in the practical communication network, since the network environment usually changes with a slower time constant than the communication period of the networked systems. That is to say, the delays of two successive transmissions are highly correlated to each other. A way to reflect such correlations between the transfer delays is using the Markov chain. To be specific, the communication delay  $\tau_k$  is modeled as a homogeneous Markov chain, which takes values in a finite set  $M = \{0, 1, \dots, n\}$  with the transition probability matrix being  $\Pi = [\pi_{ij}]_{n \times n}$ , i.e.,

$$\pi_{ij} = \mathbb{P}(\tau_{k+1} = j | \tau_k = i), \quad \text{and} \quad \sum_{j=1}^n \pi_{ij} = 1, \quad \text{for } i, j \in M.$$

In [40], the stabilization problem for NCSs with Markov delays in both sensor-to-controller and controller-to-actuator loops has been investigated. By transforming the closed-loop systems into Markov jump linear systems with two modes, the necessary and sufficient conditions on the existence of stabilizing controllers have been established. Further studies in [41] have extended the results in [40] to a more general output feedback stabilization problem. In [6], the fault detection problem has been addressed for a class of networked systems with Markov communication delays, and a robust fault filter with desired  $H_\infty$  performance has been designed.

### 1.2.3 Packet Dropout

Another significant challenge in NCSs is that the data packets may be dropped or lost while transmitted over the communication network. The packet dropout can be caused by a variety of reasons, for instance, an excessively long transmission delay, packet reordering, the disconnection of networks, transmission errors, and so on. The research interest on this topic usually focuses on the modeling of packet dropouts, the optimality of the controller/filter, and the stability and stabilization of networked systems. An arguably popular approach to describe packet dropouts is