



中國人民大學  
RENMIN UNIVERSITY OF CHINA

# 复杂批次系统智能学习控制

## 1. Introduction



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金融计算与数字工程教育部工程研究中心

# OUTLINE



## 研究背景

制造强国  
迭代学习控制  
五个研究维度



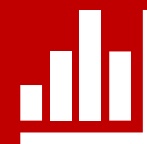
## 学术贡献

学术贡献图  
不完备数据驱动  
过程性能增强



## 综述论文

专题综述  
不完备数据  
现状与未来



## 数据资料

学术论文  
专著专利等

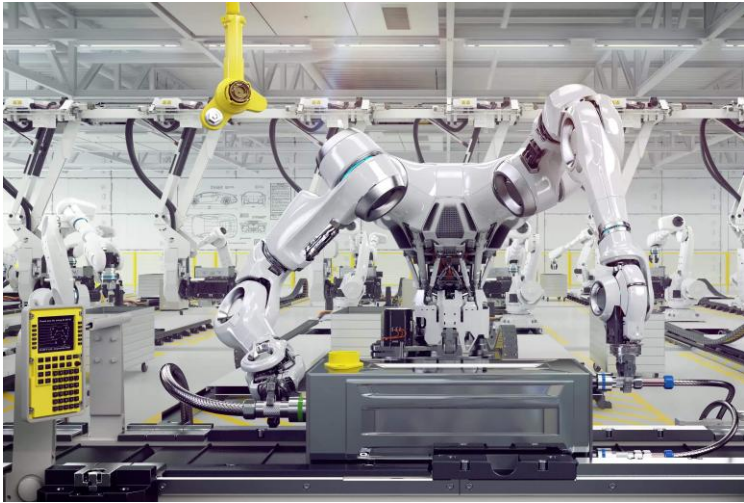


## 高举中国特色社会主义伟大旗帜 为全面建设社会主义现代化国家而团结奋斗

——在中国共产党第二十次全国代表大会上的报告

(二) 建设现代化产业体系。坚持把发展经济的着力点放在实体经济上，推进新型工业化，加快建设**制造强国**、质量强国、航天强国、交通强国、网络强国、数字中国。实施产业基础再造工程和重大技术装备攻关工程，支持专精特新企业发展，**推动制造业高端化、智能化、绿色化发展**。巩固优势产业领先地位，在关系安全发展的领域加快补齐短板，提升战略性资源供应保障能力。推动战略性新兴产业融合集群发展，构建新一代信息技术、人工智能、生物技术、新能源、新材料、高端装备、绿色环保等一批新的增长引擎。……

# 迭代学习控制



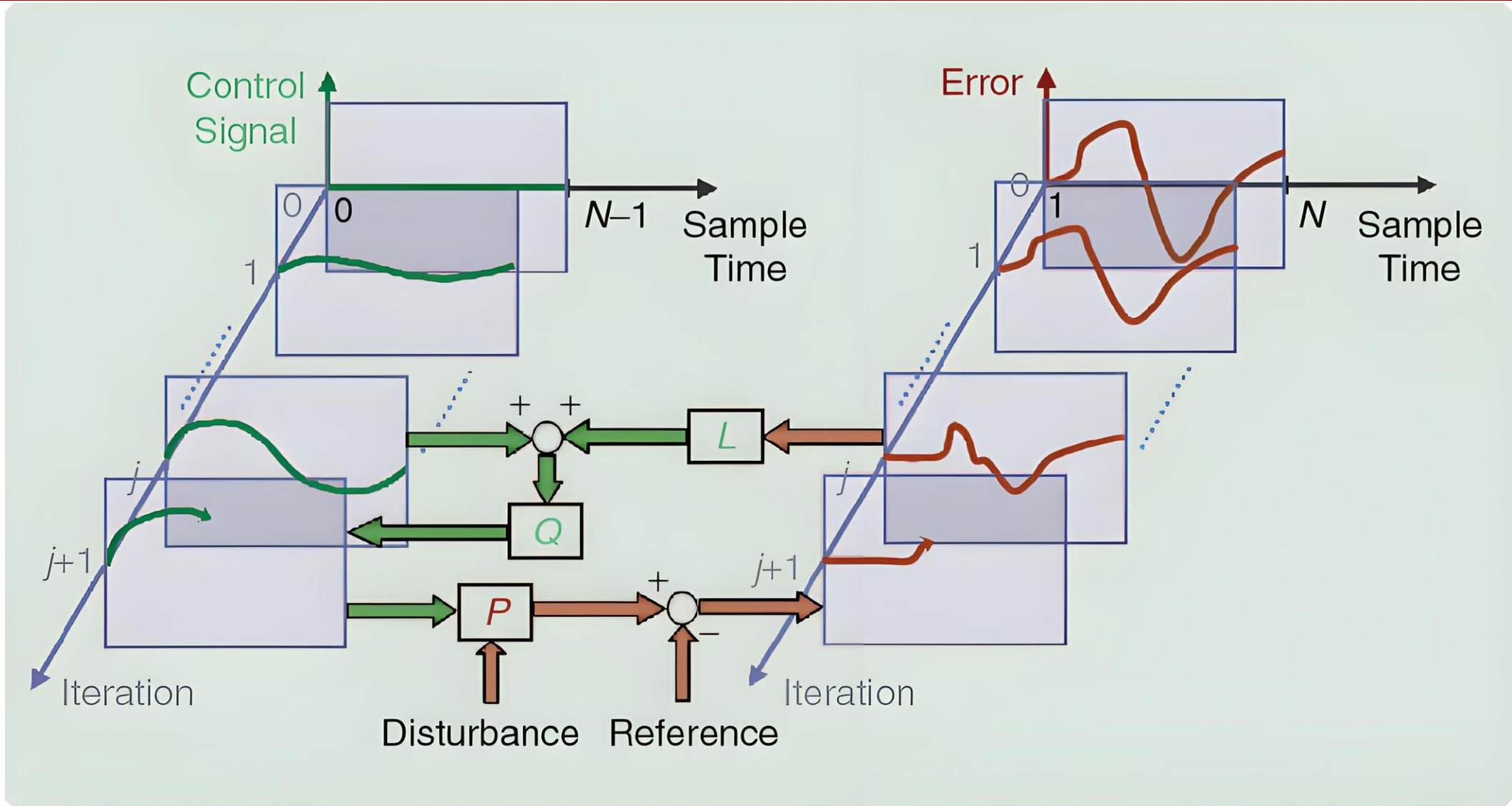
生产制造过程的一个基本特点是**批次化**

传统控制方法多是设计实时反馈型控制方案  
在不同批次间控制性能难以提升

**迭代学习控制**

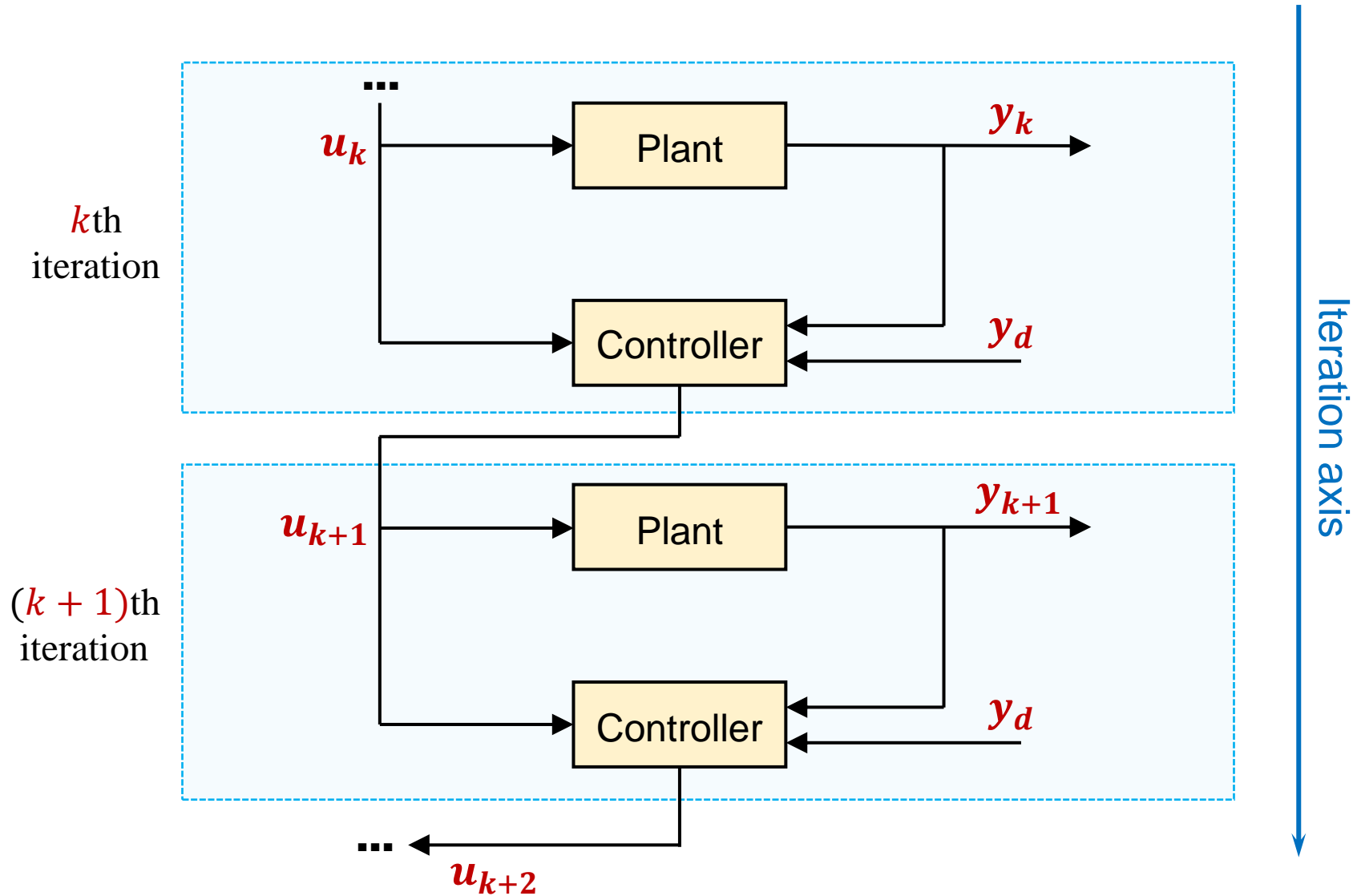


# 迭代学习控制

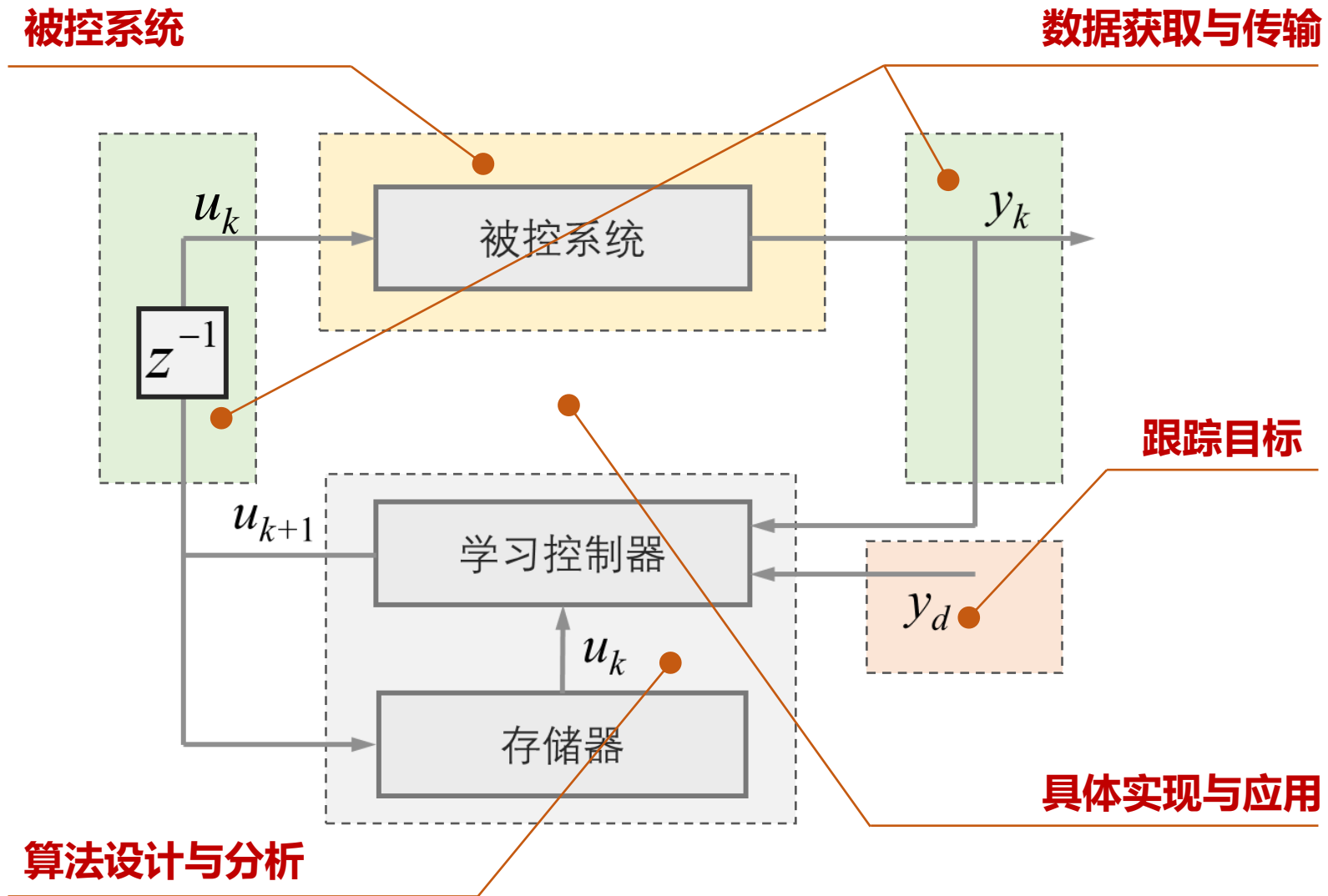


D. A. Bristow, M. Tharayil and A. G. Alleyne. A survey of iterative learning control: A Learning-based Method for High-performance Tracking Control. *IEEE Control Systems Magazine*, 2006.

# 迭代学习控制



# 迭代学习控制

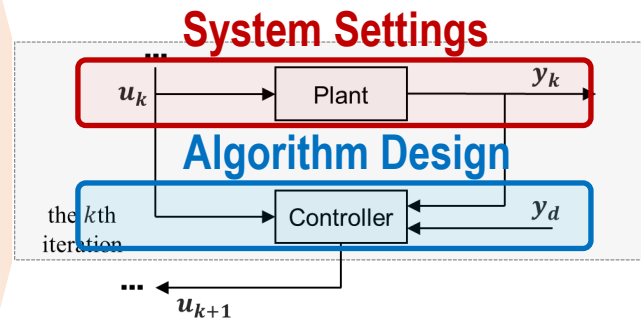


## Information Oriented ◦ 不完备数据驱动控制

RLP: Robust Learning Principle  
鲁棒学习原理 ◊ 信息缺失

RIM: Recovery Information Mechanism  
重构信息机制 ◊ 信息漂移

JLF: Joint Learning Framework  
联合学习框架 ◊ 信息复用



## Performance Oriented ◦ 过程性能增强控制

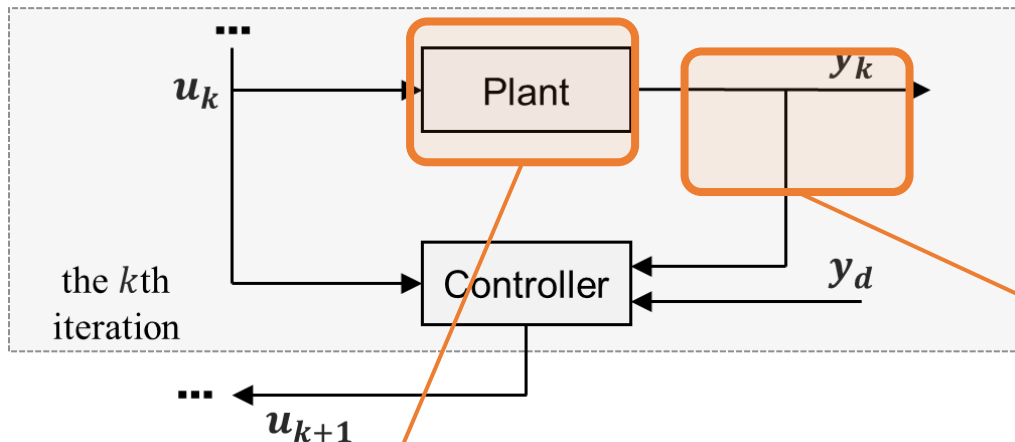
VGD: Variable Gain Design  
变增益设计 ◊ 性能驱动

NUS: Nonlinear Update Scheme  
非线性更新方案 ◊ 性能变革

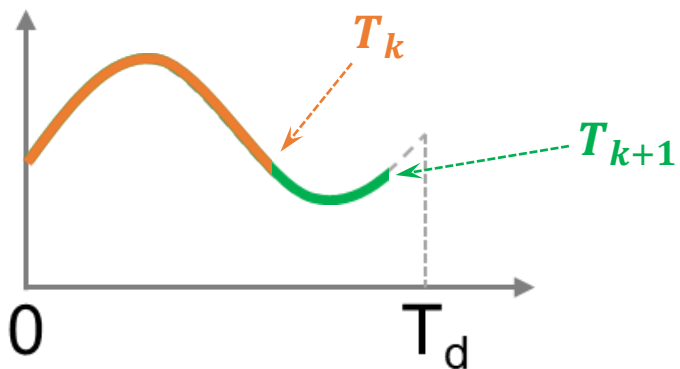
OLS: Optimized Learning Strategy  
优化学习策略 ◊ 性能优化

场景  
难题

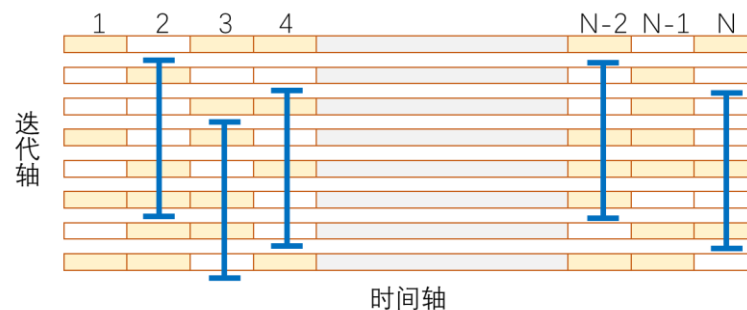
数据随机不完备导致梯度漂移，致使传统算法设计无法实现精准收敛



批次随机变长度



随机数据丢包



## 未知随机数据不完备场景下，设计鲁棒算法实现渐进精确跟踪

### □ 数据丢包 ↘ 在数据丢包/延迟等客观不完备数据条件下，如何实现高精度的控制性能？

- 建模：建立有限批次序列、马氏链两种有批次依赖性丢包模型，去除独立性的强假设 (JAS 2018)
- 设计：提出存储器数据更新机制与算法迭代触发机制，建立连续型学习更新算法，解决了有限存储/丢包/延迟等复杂耦合情形下的学习控制问题 (TNNLS 2018, IS 2017)
- 分析：证明了两侧丢包情形下，计算输入与实际输入之间的异步性具有马尔科夫性质 (TAC 2017)；建立了强概率意义下的收敛性分析框架 (TNNLS 2018, IS 2017)

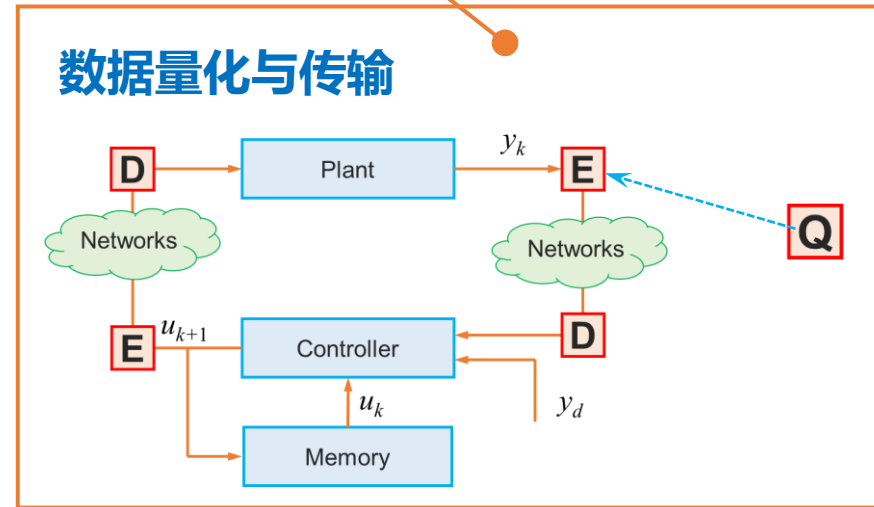
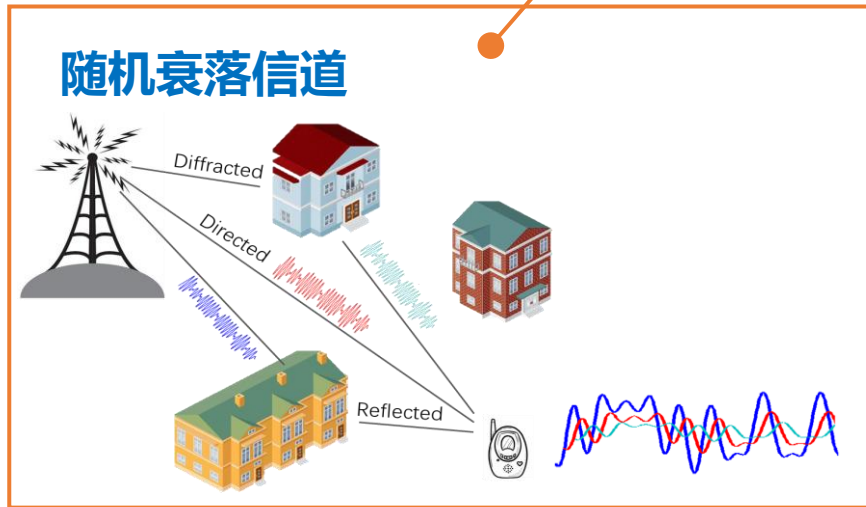
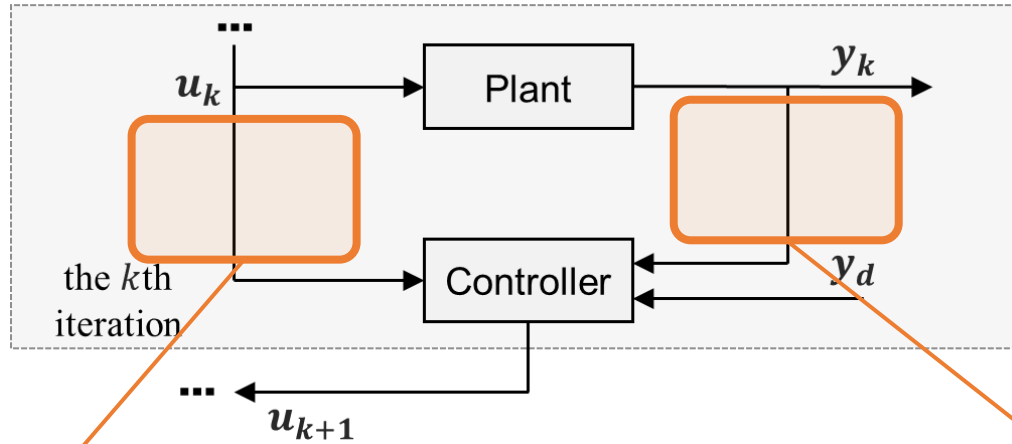
### □ 批次变长度 ↘ 在批次长度不等的条件下，如何预测缺失过程并进行控制性能比较？

- 建模：建立基于马氏链的离散动态模型与基于概率分布函数的连续动态模型 (TAC 2022, ARC 2019)
- 设计：建立基于随机平均算子的历史数据回溯机制预测缺失过程 (SCL 2017)
- 分析：建立离散系统基于随机切换系统的递推计算分析方法 (AUT 2016)，与连续系统基于虚拟误差的新型复合能量函数 (TNNLS 2019, RNC 2019)，实现了信息量不等条件下的性能比较

# 重构信息机制

场景  
难题

所获取的数据较真实信号存在不确定或随机偏移，蕴含信息与原始信息不等价



### 基于不准确数据重构出原始真实信号或其等价信息

#### □ 量化传输 ↘ 如何在有效降低对数据量获取需求的同时，实现对原始信号的重构？

- 均匀量化：建立了编解码机制与有限层级均匀量化器相结合的综合方法 (TASE 2020, TCYB 2022)，设计了编解码机制缩放参数的自适应机制 (TCYB 2025)，实现了信号传递的渐进精确重构
- 球极坐标量化：提出了融合编解码机制的球极坐标量化方法，通过迭代动态调整支撑球半径来规避量化器饱和问题且不需要引入缩放参数 (TCYB 2025, RNC 2024)
- 概率量化：提出了概率量化机制 (TNNLS 2021)，结构比编解码机制更为简洁，实现渐进零误差跟踪性能

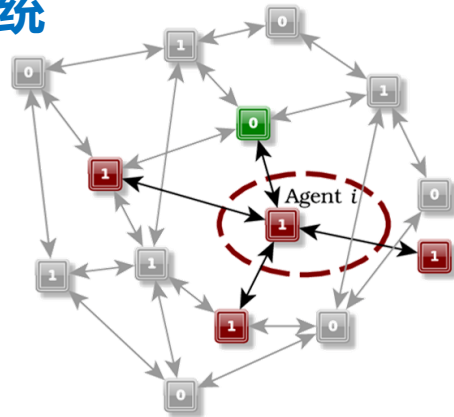
#### □ 衰落信道 ↘ 在信号幅值发生随机漂移的条件下，如何实现等价信息的有效提取用于学习？

- 统计信息已知：建立输入信号的三种迭代平均机制，保证了系统动态过程的平稳性，明确刻画了学习速率与跟踪精度之间的折中平衡关系 (TAC 2021, TNNLS 2020, TNNLS 2021)
- 统计信息未知：建立基于随机迭代差分的综合梯度估计方法 (TNNLS 2021) 与基于测试信号的迭代估计机制，用于有偏信息校正 (TNNLS 2022)
- 统计信息变化：刻画实现渐进精确跟踪的最小信息需求，建立仅基于单批次有限测试信号的均值逆的无偏估计，实现了关键信息的提取与校正 (TAC 2023)

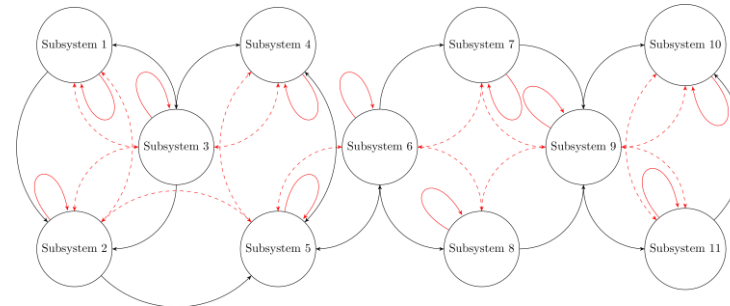
场景  
难题

由多个个体组成的复杂网络系统，如何统筹个体信息提升控制性能

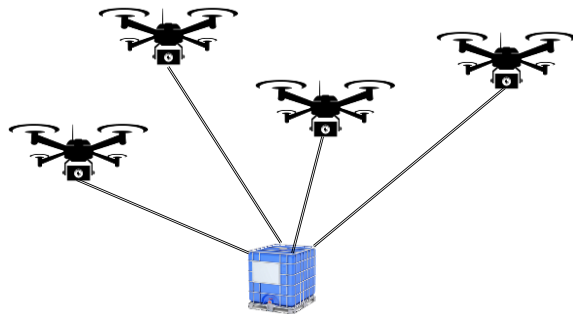
多智能体系统



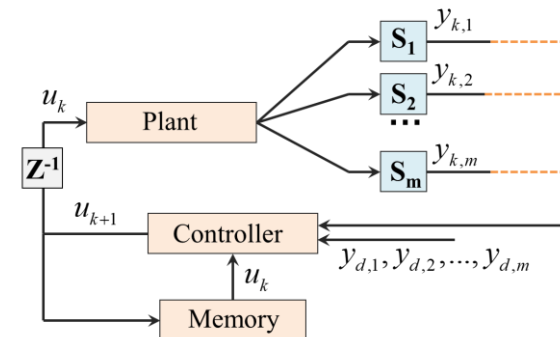
大规模内联系统



多个体合作任务



多传感器系统



## 多种拓扑框架和信息交换模式下的联合学习理论

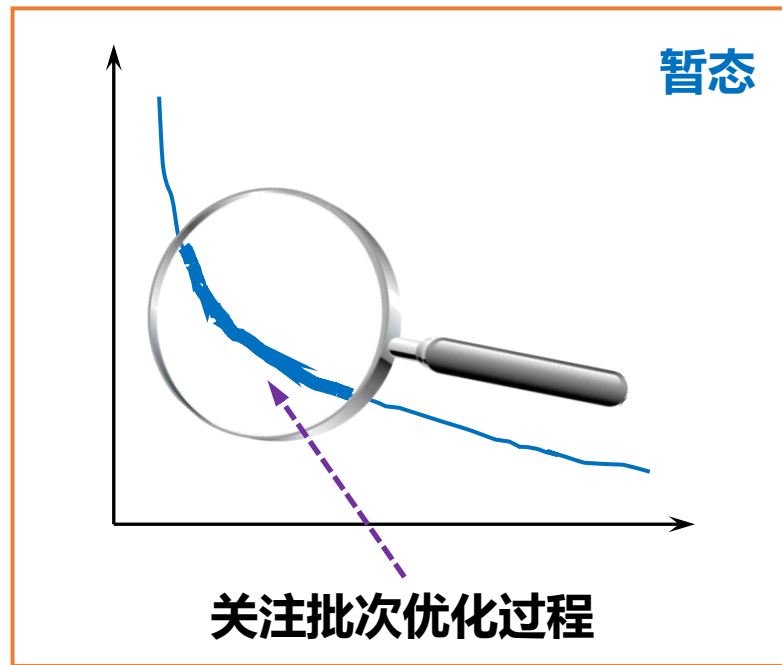
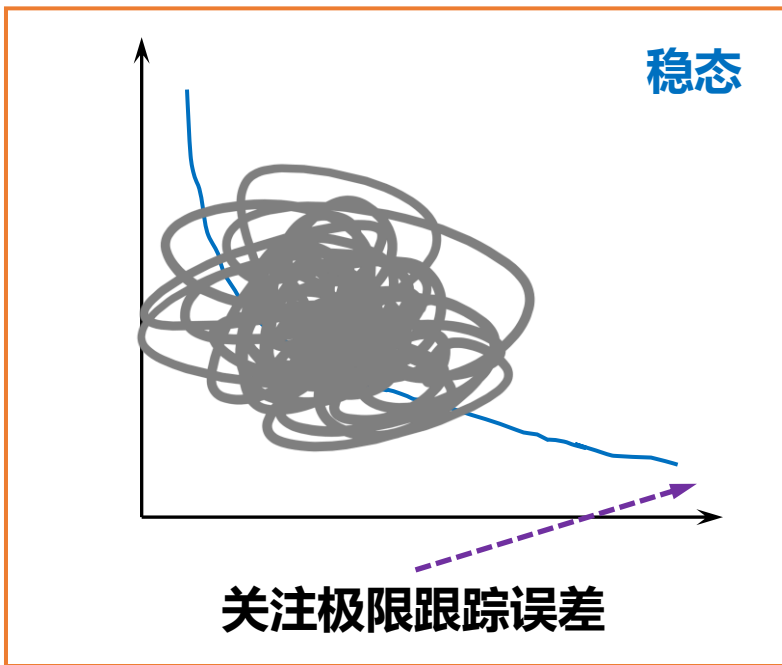
### 联合学习 如何针对不同类型复杂系统的结构特点，建立高效联合学习模式？

- 针对异质受约束**非线性多智能体系统**，提出了**分布式自适应学习协同控制方法**，建立有限批次学习协同跟踪上界的数学表达，揭示了系统结构、算法参数与跟踪精度之间的关系 (**Auto 2018, RNC 2019**)
- 针对**大规模非线性内联系统**，给出了**状态耦合矩阵**的定义和计算方式，建立**异步分散式学习控制算法**，给出了新的分析方法 (**IS 2023, Auto 2012**)
- 针对**多系统合作学习模型预测控制**问题，可根据实际场景及限制约束自主产生学习目标，提出了一类可高效计算的算法求解相关问题 (**ISA Trans 2022**)
- 针对多传感器系统，定义了**不相容多目标跟踪问题**并给出可行解数学刻画，建立了具有数据鲁棒性的**融合型迭代学习控制 (TCYB 2021)**，实现了**帕累托最优解集单调下降**迭代学习 (**TCYB 2024**)，建立了**基于用户偏好的迭代学习方案 (TAC 2026)**，解决了不相容多目标学习跟踪问题

# 变增益设计

场景  
难题

增益设定不依赖于系统运行过程中的实时表现，缺乏有效的整定方法



增益产生机制

控制精度 收敛速度

算法  $u_{k+1}(t) = u_k(t) + \gamma L_t \epsilon_k(t+1)$

## 面向系统综合性能提升的随机数据驱动适应型增益设计机制

### □ 增益设计 → 如何基于实际运行状态自主计算增益，实现控制精度与收敛速度的有效平衡？

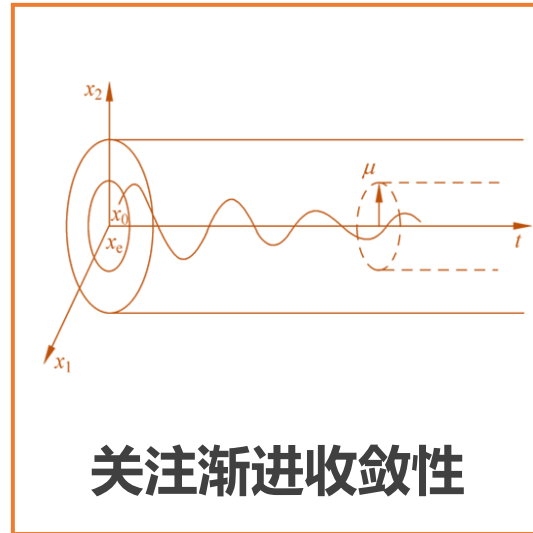
- **最优增益**: 建立基于估计跟踪性能的**递推最优增益机制**，基于阶的估计给出**收敛速率精确估计 (TNNLS 2022)**，给出了大规模内联系统**分散式最优增益**递推计算方法 (IS 2023)
- **自适应增益**: 建立仅基于跟踪误差的**自适应增益机制**，可根据系统运行性能自主切换学习模式 (TAC 2020)，早期阶段增益保持不变，后期阶段切换为随机型衰减序列；为**随机点对点跟踪问题与随机变批次长度问题**给出了变形版本 (TAC 2022, TNNLS 2024)
- **多阶段增益**: 建立基于累积性噪声影响和压缩性输入误差相比较的**多阶段增益自调节机制**，引入纵向拉伸参数和横向拉伸参数，提出三种加速调节机制，平衡了跟踪性能与收敛速度两方面的需求 (TCYB 2023, TNNLS 2024)
- **矩阵增益**: 基于误差自适应机制提出了含暂态过程加速效果的**自适应矩阵增益**设计方案 (TCYB 2024)，基于跟踪误差大小动态分配权重提出了**自适应误差加权机制**，均可模块化集成至现有多种更新方案，构成**数据驱动的非线性更新律**，加速暂态收敛过程 (TAC 2026, TCYB 2025)

# 非线性更新方案

场景  
难题

绝大部分迭代学习更新律采用比例型更新结构，本质上限制了其学习能力

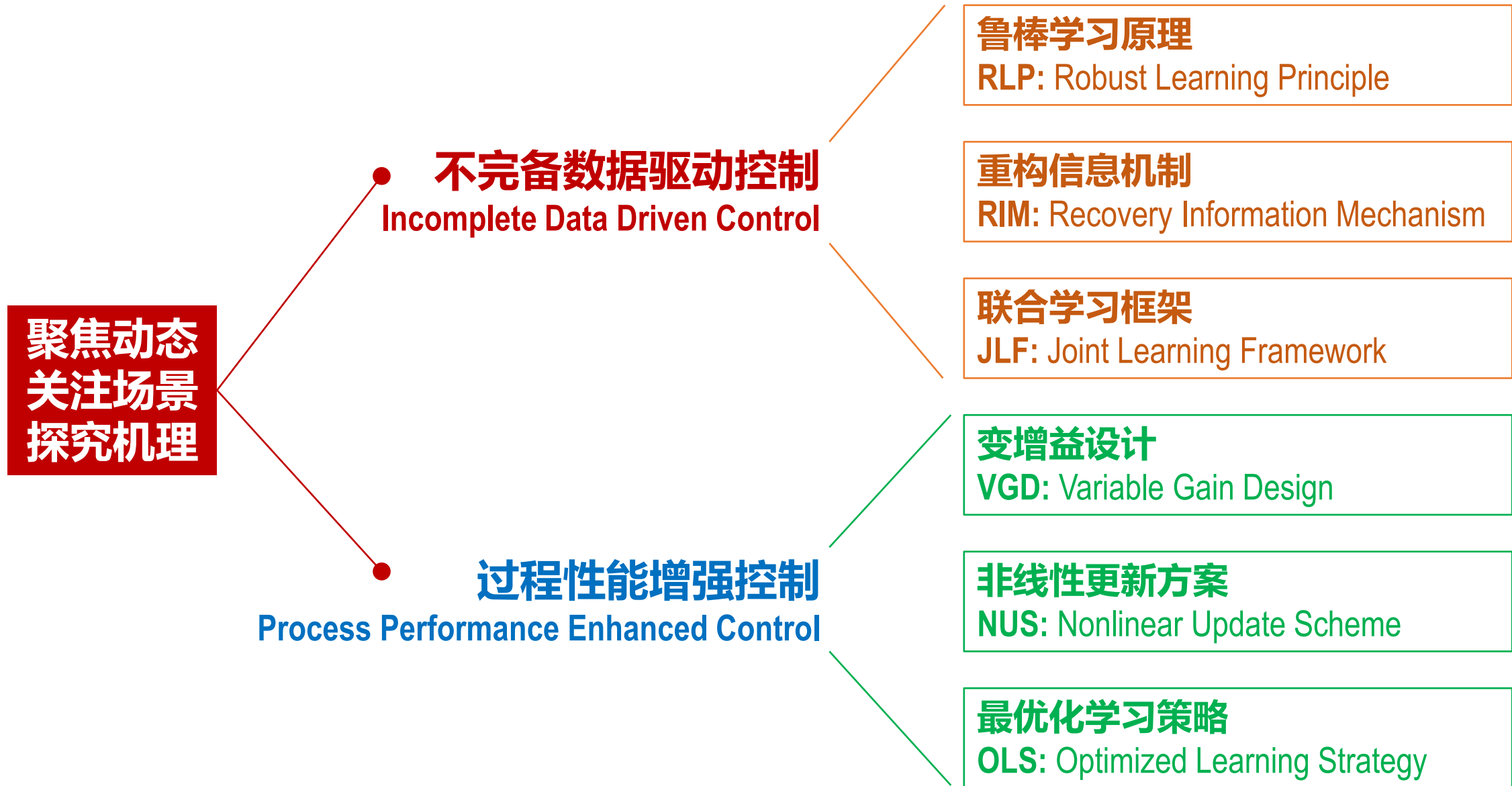
$$u_{k+1}(t) = u_k(t) + \rho L e_k(t + 1)$$



## 综合强化学习能力、提升收敛速度、改善控制性能三需求的更新方案

### □ 非线性更新 ↘ 如何建立非线性学习结构特征的迭代更新算法，刻画其动态演化过程？

- 首次为整数阶系统提出了**纯分数次幂学习控制算法**，建立了基于**非线性映射**的收敛性分析框架，给出了**极限环**的计算方法 (JAS 2023)
- 提出了基于分数次幂更新律与比例型更新律的**多阶段切换型学习控制算法**，切换点独立于系统信息，建立了扰动非线性递归分析方法 (TASE 2024)
- 提出了同时包含分数次幂更新项与比例更新项的**复合学习控制算法**，基于扰动非线性映射原理建立收敛性分析，刻画了迭代**初始值与收敛极限**的对应关系，实现了**超线性收敛**速度 (TAC 2025, TCYB2025)
- 提出了结合**高阶与低阶分数次幂**的学习控制算法，给出了参数设计的**同向学习机制与反向学习机制**，建立了两种机制下的**正向演化不变集** (submitted)



Journal of Process Control

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## Survey on stochastic iterative learning control

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<sup>a</sup> College of Information Science and Technology, Beijing University of Chemical Technology

ARTICLE INFO

ABSTRACT

Iterative learning control (ILC) with incomplete information and associated control system design, which is a frontier of the ILC field. The incomplete information, including passive and active types, can cause data loss or fragment due to various factors. Passive incomplete information refers to incomplete data and information caused by practical system limitations during data collection, storage, transmission, and processing, such as data dropout, delays, disordering, and limited transmission bandwidth. Active incomplete information refers to incomplete data and information caused by man-made reduction of data quantity and quality on the premise that the given objective is satisfied, such as sampling and quantization. This survey emphasizes two aspects: the first one is how to guarantee good learning performance and tracking performance with passive incomplete data, and the second is how to balance the control performance index and data demand by active means. The promising research directions along this topic are also addressed, where data robustness is highly emphasized. This survey is expected to improve understanding of the restrictive relationship and trade-off between incomplete data and tracking performance, quantitatively, and promote further developments of ILC theory.

**Index Terms**—Iterative learning control, incomplete information, data robustness, data dropout, varying lengths, sample control, quantized control.

1. Introduction

In our daily lives, the ability to repeatedly work on a given task would lead to constant improvements. For example, in basketball set shooting, as the number of attempts increases, the shooter able to increase the hit ratio since he/she may adjust the angle and speed to reduce the shooting deviation shot by shot. The basic reason for this is that we are able to learn from experiences and subsequently improve our behaviors.

This basic cognition has motivated research on iterative learning control (ILC). That is, ILC is a control method that improves its control performance by learning from previous control performance. Specifically, ILC is usually designed for systems that are able to complete some task over a fixed time interval and perform the repeatedly. In such systems, the input and output information past cycles, as well as the tracking objective, are used to formulate the input signal for the next iteration, so that the tracking performance can be improved as the number of cycles increases infinitely. Thus, ILC has the following features: (1) the system can finish a task in a limited time, (2) the system can be reset to the same initial value, and (3) the tracking objective is iteration-invariant. The main idea of ILC is shown in Fig. 1.

In Fig. 1,  $y_d$  denotes the reference trajectory. Based on the input of the  $k$ th iteration,  $u_k$ , as well as the tracking error  $e_k = y_d - y_k$ , the

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http://dx.doi.org/10.1016/j.procon.2014.04.013  
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JOURNAL OF IIR CLASS FILES, VOL. 11, NO. 4, DECEMBER 2012

## Iterative Learning Control for Informatic

Dong Shen, Se

Abstract—This paper conducts a survey on iterative learning control (ILC) with incomplete information and associated control system design, which is a frontier of the ILC field. The incomplete information, including passive and active types, can cause data loss or fragment due to various factors. Passive incomplete information refers to incomplete data and information caused by practical system limitations during data collection, storage, transmission, and processing, such as data dropout, delays, disordering, and limited transmission bandwidth. Active incomplete information refers to incomplete data and information caused by man-made reduction of data quantity and quality on the premise that the given objective is satisfied, such as sampling and quantization. This survey emphasizes two aspects: the first one is how to guarantee good learning performance and tracking performance with passive incomplete data, and the second is how to balance the control performance index and data demand by active means. The promising research directions along this topic are also addressed, where data robustness is highly emphasized. This survey is expected to improve understanding of the restrictive relationship and trade-off between incomplete data and tracking performance, quantitatively, and promote further developments of ILC theory.

**Index Terms**—Iterative learning control, incomplete information, data robustness, data dropout, varying lengths, sample control, quantized control.

1. INTRODUCTION

MANY practical systems follow the same operation mode where they repeatedly complete a given task in a fixed time interval. For instance, the industrial production process generally consists of successive batches of production task that is, the system completes a production batch following a given procedure within the desired time interval and then repeats it again and again. For such systems that can be clearly divided into successive operation batches, if the operation time lengths of each batch are identical and the operation circumstances of different batches are similar, then we can fully utilize the operation data and experience to adjust the active strategy for the next batch. This basic concept of “learning” motivates the proposal and developments of iterative learning control (ILC), which is now an important branch of intelligent control [1]. In other words, ILC is a typical control strategy mimicking the learning process of the human being, where the pivotal idea is to continuously learn the inherent repetitive factors of system operation processes based on various data.

This work is supported by National Natural Science Foundation of China (61673045) and Beijing Natural Science Foundation (4152040).  
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Manuscript received February 10, 2018, revised April 02, 2018, accepted May 02, 2018.

Unmanned Systems, Vol. 0, No. 0 (2018) 1–17  
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## A Technical Overview of Recent Progress in Iterative Learning Control

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<sup>a</sup> College of Information Science and Technology, Beijing University of Chemical Technology  
<sup>b</sup> School of Intelligent Systems Engineering, Sun Yat-sen University, Guangzhou 510275, China

Review article

A survey on iterative learning control with varying lengths: Model, synthesis, and convergence analysis

Dong Shen<sup>a,\*</sup>, Xuefang Li<sup>b</sup>

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<sup>b</sup> School of Intelligent Systems Engineering, Sun Yat-sen University, Guangzhou 510275, China

ARTICLE INFO

ABSTRACT

The nonuniform trial lengths in iterative learning control (ILC) have attracted much attention in recent years. This survey reviews recent progress on stochastic ILC with varying lengths. The fundamental principles of ILC are reviewed in three parts: recent progress on stochastic ILC are reviewed in three parts: active, respectively. Three major approaches, i.e., expectation-based method, are clarified. Promising research directions are also presented.

**Keywords:** Stochastic iterative learning control; stochastic systems filtering; stochastic approximation.

1. Introduction

While starting basketball shooting from a fixed position, we may fail for the first several shots as we have insufficient information about the distance and environments. However, after each shot, we can learn the information about the basket shooting process and then improve our shot angle and position. Thus, we can shoot more and more accurate until we hit the basket. The inherent principle is that we can learn from past shoots or experiences. This learning ability helps us in almost every skill such as swimming, driving, and painting. In basic cognition of learning can be also applied to the industrial systems such as robotics and batch processes. For the latter of systems, the operation information from previous batches is fully utilized to improve the performance. In particular, those systems that operate in a fixed time interval, which is called an iteration, and repeat the operations successively operation information including input and output as well as tracking reference can be utilized to revise the input signal the next iteration. As a consequence, the tracking performance gradually improved as the iteration number increases. This type of control is called iterative learning control (ILC), motivated by the basic concept of learning, which has been an important branch of intelligent control. Clearly, ILC is a typical control strategy that mimics the learning process of human being in which the pivotal idea is to continuously learn the inherent repetitive factors of system operation processes.

Comparing ILC with other traditional control methods such as adaptive control and robust control, we find that

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https://doi.org/10.1016/j.ics.2019.10.003  
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Annual Review of Control and Adaptive Systems

## History Making in Iterative Learning Control for High-Speed Trains

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Review article

A survey on iterative learning control with varying lengths: Model, synthesis, and convergence analysis

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ARTICLE INFO

ABSTRACT

The nonuniform trial lengths in iterative learning control (ILC) have attracted much attention in recent years. This survey reviews recent progress on stochastic ILC with varying lengths. The fundamental principles of ILC are reviewed in three parts: recent progress on stochastic ILC are reviewed in three parts: active, respectively. Three major approaches, i.e., expectation-based method, are clarified. Promising research directions are also presented.

**Keywords:** Stochastic iterative learning control; stochastic systems filtering; stochastic approximation.

1. Introduction

While starting basketball shooting from a fixed position, we may fail for the first several shots as we have insufficient information about the distance and environments. However, after each shot, we can learn the information about the basket shooting process and then improve our shot angle and position. Thus, we can shoot more and more accurate until we hit the basket. The inherent principle is that we can learn from past shoots or experiences. This learning ability helps us in almost every skill such as swimming, driving, and painting. In basic cognition of learning can be also applied to the industrial systems such as robotics and batch processes. For the latter of systems, the operation information from previous batches is fully utilized to improve the performance. In particular, those systems that operate in a fixed time interval, which is called an iteration, and repeat the operations successively operation information including input and output as well as tracking reference can be utilized to revise the input signal the next iteration. As a consequence, the tracking performance gradually improved as the iteration number increases. This type of control is called iterative learning control (ILC), motivated by the basic concept of learning, which has been an important branch of intelligent control. Clearly, ILC is a typical control strategy that mimics the learning process of human being in which the pivotal idea is to continuously learn the inherent repetitive factors of system operation processes.

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https://doi.org/10.1016/j.ics.2019.10.003  
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## History Making in Iterative Learning Control for High-Speed Trains

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Abstract—With the development of high-speed trains (HSTs) has attracted much attention in engineering practice. The core task that imitates human learning behavior, iterative tracking problems. Owing to the characteristics of ILC, ILC is regarded as a promising strategy for HSTs. Therefore, various ILC schemes for HSTs and provides an overview of the existing ILC schemes for HSTs into two categories: whether they are based on the train dynamics and model-free ILC, respectively. Next, encounter various issues, we introduce them are summarized from three aspects: active. Finally, we present promising directions provide a general concept of the current

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https://doi.org/10.1016/j.ics.2026.03.001  
Received 8 January 2026; Received in revised form 1 March 2026; Accepted 1 March 2026  
Available online 4 March 2026  
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ARTICLE IN PRESS

ISA Transactions xxx (xxxx) xxx

Contents lists available at ScienceDirect

ISA Transactions

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Research article

## Advances in iterative learning control: A recent five-year literature review\*

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HIGHLIGHTS

- First 5-axis survey of ILC progress focusing on recent five-year literature review.
- Per-axis milestones, gaps and future directions give researchers a one-stop trend.
- Review links mature ILC theory to practical deployment needs.

ARTICLE INFO

ABSTRACT

Iterative learning control (ILC) is a control strategy specifically devised for finite-length batch processes that can be repeatedly executed. By iteratively refining the input signal across successive system trials, ILC enables accurate tracking of a predefined reference trajectory. Since its inception, this control methodology has evolved over four decades into a relatively mature and comprehensive theoretical framework. Nevertheless, in the past decade, the field has lacked systematic review and in-depth discussion on the overall progress of the field, with only a handful of studies offering limited retrospectives within specific subdomains. To provide a holistic understanding of the current state of the art and to identify promising directions for future investigation, this paper presents a literature review of recent key developments from five essential dimensions: system dynamics and settings, signal acquisition and transmission, reference trajectory, algorithm design and analysis, and implementations and applications. For each dimension, we summarize the major advancements and representative contributions, followed by critical discussions and forward-looking perspectives. This review aims to help researchers and practitioners in grasping the prevailing research trends and to inspire further theoretical and applied developments in ILC.

1. Introduction

Batch processing serves as a core manufacturing paradigm in industrial production, characterized by repetitive task execution within defined time cycles. Typical implementations encompass semiconductor wafer processing, automated assembly lines, additive manufacturing systems, and chemical batch reactors. This operational principle extends to other real-world systems. Urban subway networks and high-speed rail systems exemplify cyclic operational patterns, maintaining fixed routes and schedules through recurring cycles. These systems demonstrate precise repeatability in process execution with consistent temporal parameters. While complex systems may deviate from strict periodicity due to multiple influencing factors, they retain significant repetitive characteristics. Urban traffic networks exhibit this pattern, displaying repetitive weekday operational modes where morning/evening rush hours maintain comparable timing and duration daily. Macroscopically, consecutive days' traffic patterns demonstrate notable similarity in operational processes.

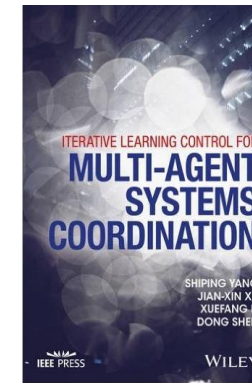
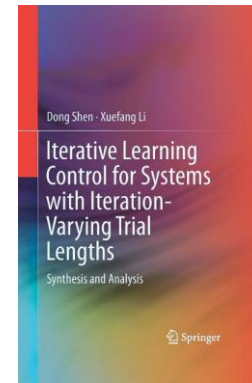
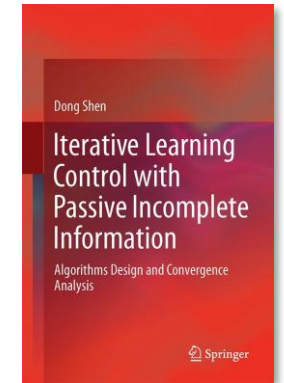
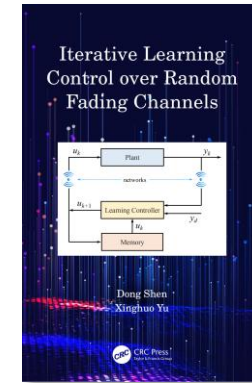
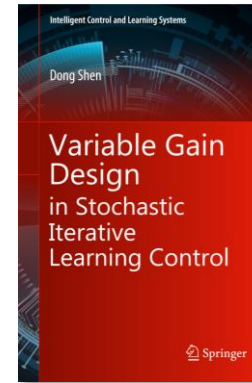
The operation processes of all the aforementioned systems exhibit a fundamental characteristic of batch processes. Specifically, each system completes one batch within a finite time and repeats this process continuously, with repeated batches being either identical or highly similar. This raises the question: can data from completed batches improve the performance of subsequent batches? For a system that operates repetitively, it is possible to establish an iterative learning mechanism that uses data from previous batches to generate control signals for the next batch, enhancing control performance over time. This idea has inspired the academic community to propose iterative learning control (ILC) methods.

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https://doi.org/10.1016/j.isatra.2026.03.001  
Received 8 January 2026; Received in revised form 1 March 2026; Accepted 1 March 2026  
Available online 4 March 2026  
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Please cite this article as: Dong Shen et al., ISA Transactions, https://doi.org/10.1016/j.isatra.2026.03.001

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## Acknowledgement

This work is supported by National Natural Science Foundation of China (62573422, 62173333, 61673045, 61304085) and Beijing Natural Science Foundation (Z210002, 4152040).

