Data-Driven Control and Learning Systems

MANY industry processes, aerospace systems, transportation systems, power grid systems, etc., are becoming more and more complex. Modeling the accurate physical models for these plants using first principles may be impossible or infeasible. Even if their physical models are available, they may be too complex to be tractable for controller design, system monitoring, performance evaluation, etc. However, huge amounts of measured process data can easily be collected due to the well-developed information technology, both in the form of stored historical data from prior measurements and online data in real time during process runs. Thus, it would be very significant if we can make full use of those online or offline process data to directly design controller, predict and assess system states, evaluate performance, make decisions, perform real-time optimization, and conduct fault diagnosis. For this reason, the establishment and development of data-driven control (DDC) theory and methodology are the urgent issues both in theory and applications.

DDC means the control theory and method in which the controller is designed by directly using online or offline I/O data obtained from the controlled system or knowledge from data processing, instead of first modeling the controlled plant and then designing the controller using the process physical model obtained. Meanwhile, the stability, convergence, and robustness could be guaranteed by rigorous mathematical analysis under certain reasonable assumptions [item 1) in the Appendix]. Data-driven learning systems imply that the system functions, such as modeling, decision, optimization, scheduling, monitoring and diagnosis, maintenance, are all implemented only by using the data or the knowledge from the data when the physical model is unavailable [items 2) and 3) in the Appendix].

The tasks of the DDC are essentially the same as model-based control and method except for unavailability of the plant model. However, data-driven methods aim to address the system control or decision issues through direct using the process data or knowledge learning/mining from the data, and meanwhile to get rid of the challenging issues of model-based theory and method, for instance, modeling and robustness, the big gap between the model-based theory and application. Model-based methods and data-driven methods are two inseparable parts of a complete paradigm for scientific research and problem-solving theory, and they can work individually or in a complementary manner, which will enable us to have the ability to deal with all the control and decision problems arisen from theoretical or practical processes with or without physical models.

In the last decade, many scholars and scientists have put forth great effort in this new cutting-edge topic by launching Special Issues in prestigious journals [items 4)–7) in the Appendix]. However, this new emerging area grows so fast that there are many new works have been developed every year. Thus, the objective of this "Special Section on Data-Driven Control and Learning Systems" of the IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS is to provide the latest advances both in theory and application. It includes 26 papers, and these papers are roughly categorized into two groups, namely, "data-driven control," and "data-driven learning systems." The brief introductions for all papers are summarized below.

I. DATA-DRIVEN CONTROL

There are very few systematic works in the field of DDC since it is a new emerging domain in the system control community. Item 8) in the Appendix presents a bird's-eye view of the model-free adaptive control (MFAC), one of the existing systematic works in DDC, for the unknown discrete-time nonlinear systems with applications, including the main differences between the model-based control and DDC methods, the virtual equivalent dynamic linearization (DL) as a fundamental tool for MFAC designing and analysis, the prototype MFAC schemes by using the DL to unknown nonlinear plant model, the alternative MFAC methods by using the DL to unknown ideal nonlinear controller, and the corresponding model-free adaptive iterative learning control methods by introducing the DL to unknown repetitive nonlinear systems as well. Finally, some perspectives on DDC methods in the information-rich age are given.

Adaptive dynamic programming (ADP) method is one of DDC methods. The following three papers focus on the ADP-based DDC designing. The consensus control problem is a hot topic in the control community recently. In item 9) in the Appendix, the optimal consensus control problem for discrete-time multiagent systems with completely unknown dynamics is investigated by utilizing a data-driven reinforcement learning method and the current and past system data, instead of traditional accurate modeling for the multi-agent systems and solving of the coupled Hamilton–Jacobi–Bellman equation. Finally, two simulation examples are provided to demonstrate the effectiveness of the proposed method.

An event-triggered control scheme for nonlinear constrained-input continuous-time systems based on the optimal policy is developed in item 10) in the Appendix. The online ADP algorithm is used to learn the optimal solution with partially unknown dynamics, and the identifier network, critic network, and actor network are employed to approximate the unknown drift dynamics, the optimal value, and the optimal policy, respectively. Stability of the closed-loop system and convergence of the neural networks to the optimal solutions are proved by

Digital Object Identifier 10.1109/TIE.2017.2653767

Lyapunov analysis. In the end, an under-actuated overhead crane system is used to demonstrate the performance.

In item 11) in the Appendix, a novel mixed iterative ADP algorithm is proposed to solve the optimal battery energy management and control problem in smart residential microgrid systems. Based on the data of the load and electricity rate, two iterations called P-iteration and V-iteration are constructed. The V-iteration is implemented based on value iteration aiming to obtain the iterative control law sequence in each period, and the P-iteration is implemented based on policy iteration to update the iterative value function according to the iterative control law sequence. Properties of the developed mixed iterative ADP algorithm are analyzed and the numerical comparison results are given to illustrate the performance of the algorithm.

For theoretical studies, the following two papers bring some new results in DDC system design. An indirect data-driven trajectory tracking control problem for a class of unknown nonlinear discrete-time systems is presented in item 12) in the Appendix. It first establishes an approximate model of the controlled object using historical I/O data and neural network, then designs and adjusts the feedback gain matrix online using measured output data and previous estimates. The convergence analysis and simulation results using the permanent-magnet linear motor system verify the effectiveness of the presented method.

The explicit model predictive control (EMPC) has been demonstrated to be an attractive control strategy in dealing with state constraints and fast dynamics. However, the design of data-driven EMPCs with finite admissible control sets is a challenging problem. In item 13) in the Appendix, a DDC method is developed for the design of quantized EMPCs (Q-EMPCs) for time-varying output tracking of nonlinear systems using multi-class support vector machines. Extensive testing and comparison studies are performed on two-dimensional and five-dimensional benchmark examples to demonstrate the effectiveness and scalability of the scheme.

Model-based method and DDC method can help each other in a complementary manner. The following four papers address this issue. In item 14) in the Appendix, an integrated model-data-based zero phase error tracking feedforward control (ZPETFC) strategy is proposed for high-precision motion systems with complex and nonminimum phase (NMP) dynamics. The feedforward controller includes a conventional ZPETFC strategy based on the plant model, and a parameterized gain compensation filter aiming to approximate the inverse behavior of the complex and NMP dynamics. In order to compensate the modeling error and improve the tracking performance, a data-based instrumental-variable method with impulse response experiment is developed to obtain the optimal parameter vector under the existence of noise and disturbances. At the end of this paper, an experiment and comparison results on an ultraprecision wafer stage are given to demonstrate the advantages for the proposed control method.

In item 15) in the Appendix, a data-assisted modeling method for motion control of a two-link robotic fish is presented to tackle the unavailability of the complex hydrodynamics thrust mechanism. The pulse-based identification is for thrust delay, and the step response based identification is for thrust nonlinearity. Next, sliding-mode control design is presented for the robotic fish when it performs speed tracking. The experimental results verify the controller performance.

The heat exchanging unit is widely employed in many industrial processes, but difficult to control due to large disturbances. In item 16) in the Appendix, a co-working control scheme is discussed by integrating model-based control method addressing disturbance in the outer-loop supplying water temperature, and a data-driven dual-rate control method aiming to control water temperature and steam flow-rate. The stability and convergence of the proposed algorithm is analyzed and an industrial application is included.

Item 17) in the Appendix develops a lower limb exoskeleton system including mechanical structure and embedded electronic system, and a data-driven repetitive learning control scheme, to address the periodic tracking control issue with learning convergence. The proposed control scheme is implemented on the embedded electronic system and the experimental results demonstrate the performance of the whole exoskeleton system.

The problems arising from practical industrial process and equipment are the main forces to boost the advanced control technology. The following papers address some practical industrial control issues in a data-driven manner.

Most of control components in modern industry are connected through Ethernet, and the networked model is difficult to obtain due to the complexity of the practical plant. Thus, the network-based DDC problem is an important issue for the complex industrial processes. In item 18) in the Appendix, the data-driven optimal control problem for complex industrial processes described by networked double-layer structure with network-induced time delay, packet dropouts, and packet disorder in both up-link and down-link channels is investigated. The effectiveness of the overall control scheme is verified through two simulation studies.

The disturbances, uncertainties, nonlinearity, coupling, and measurement disturbances existing widely in practical industrial plants challenge the applications of model-based control methods in the field. Item 19) in the Appendix proposes a data-driven robust output tracking control (DROTC) combining advantages of sliding mode control and data-driven MFAC for stable pressure control of gas collectors of coke ovens. The novel hybrid control structure and the new data-driven sliding surface in the proposed DROTC facilitate the controller design, while the coupling, disturbances, and uncertainties are suppressed. The stability of the DROTC system is analyzed, and the simulation and experimental results are further supplied to confirm the validity.

Rougher flotation, as a crucial technology for some metallurgical engineering, is a process difficult to control. Item 20) in the Appendix focuses on a sensitive froth image feature-based control strategy for this problem, which includes an estimator of the feed grade, a preset controller, and a feedback controller. In the proposed control strategy, the selection of froth image features, the inference of feed grade, and the process uncertainties in sample data are described in detail. Finally, industrial experiments show the effectiveness of the method.

Printing systems require a high positioning accuracy while maintaining a large freedom in the reference trajectories to achieve optimal throughput. An iterative learning control scheme with a rational feedforward parameterization for an industrial flatbed inkjet printer is developed in item 21) in the Appendix. Experimental results highlight the efficacy of the proposed method in comparison with related pre-existing learning control approaches.

II. Data-Driven Learning Systems

Data-driven learning systems mainly concern the data-driven dynamic modeling and the way of improving the descriptions to estimate dynamic behavior and changing characteristics of the plant and the environment (such as disturbances) by using the process data in system design. How to use the process data and what kinds of the data should be used mark the bifurcation point for the model-based method and the DDC method. Using data widely and deeply is the only way in DDC and learning systems since the reliable physical model is unavailable.

Item 22) in the Appendix aims at handling the identification and output estimation problems simultaneously for industrial process described by finite impulse response model subjecting to randomly missing measurements. The iterative formulas to estimate the posterior distributions of missing output data and unknown parameters based on measured data are presented. The simulation example and the hybrid tank system experiment are performed to demonstrate the effectiveness of the proposed method.

Item 23) in the Appendix addresses the data-driven identification problem for the practical industrial process, where the time-varying delay described by Markov-chain model and parameters of the process model are identified by using the process I/O data by expectation-maximization algorithm. The advantages of the proposed methods are verified by numerical simulations and an evaluation on pilot-scale experiments.

In item 24) in the Appendix, a novel soft sensor modeling method based on a deep learning network that integrates denoising auto-encoders with a neural network (DAE-NN) is introduced, and an improved gradient descent algorithm is employed to update the model parameters. In the end, the DAE-NN based soft sensor is applied to estimate the oxygen content in flue gases of 1000 MW ultrasuperficial units.

The problem of distributed estimation over sensor network is a hot research topic in recent years. Item 25) in the Appendix studies the problem of distributed multitask learning over networks, where multiple node-specific parameter vectors are simultaneously inferred via collaboration among neighboring nodes using the available data in the networks. Numerical simulations are used to demonstrate the convergence and the advantages over the corresponding noncooperative learning algorithm.

Item 26) in the Appendix addresses the problem of network-based data-driven filter design for discrete-time linear systems with bounded noises and packet dropouts. An output predictor is developed to reconstruct the missing data, and then utilizing the predicted outputs and the received measurements, an almost-optimal data-driven filter with tractability is designed. Finally, the simulation results are given to illustrate the effectiveness of the proposed design.

Item 27) in the Appendix proposes a new circuit for implementing a reduced-interval type-2 neural fuzzy system using weighted bound-set boundaries (RIT2NFS-WB) with online tuning ability. The learning module in the RIT2NFS-WB(HL) tunes all the interval combination parameters in the consequent of a TSK-type rule and the weighting parameter in the weighted bound-set boundary operation, where the operation is used to simplify the type-reduction operation and reduce the circuit implementation cost. The RIT2NFS-WB(HL) with online tuning ability is suitable for handling data-driven problems with time-varying characteristics, the property has been verified through simulations of process modeling and sequence prediction.

Different from most existing myoelectric prosthetic hands using a fixed pattern recognition model to identify the user's hand motion commands, item 28) in the Appendix aims at dealing with the gradual changes in the sEMG characteristics data for hand motion commands identification. To adapt the model to the gradual changes, incremental learning technique is used for model training. To obtain a highly performed model, an ensemble model trained with negative correlation learning method is applied. The experimental results demonstrate that the proposed method can significantly improves the classification accuracy rates of hand motions and the update time.

Judder is the term used in the automotive industry to describe the longitudinal oscillation of a vehicle during its clutch system engagement. Item 29) in the Appendix proposes and implements a novel learning system for better characterization of the judder phenomenon based on a multivariate data-driven analysis from torque signals, instead of the traditional analytical modeling method. The experimental results verify that the work in this paper might reduce significantly the time of development and the cost of testing new friction materials for allowing judder-free performance on vehicles.

In item 30) in the Appendix, a novel optimal learning algorithm for partially unknown voltage-source inverters (VSIs) operating in parallel is presented. The proposed framework is based on a separate actor/critic approximator for each inverter that does not require knowledge of the values of the load, parasitic resistances, and capacitances of the VSIs, and it is tested in simulations to show its effectiveness.

The production quality, system reliability, and safety issues in the modern industrial processes are the critical aspects to be concerned. Item 31) in the Appendix develops an integrated process monitoring and control design technique for the industrial control systems. The proposed approach is an alternative realization of Youla parameterization that allows the performance of the controlled systems to be improved without modifying or replacing the predesigned control systems, while the closed-loop stability is still guaranteed. In addition, a residual signal is available for the fault detection and isolation purpose. The effectiveness and performance of the proposed approach are demonstrated on a brushless direct current motor test rig.

In item 32) in the Appendix, a novel data-driven framework using kernel partial least squares based on optimized preference matrix for fault diagnosis is presented. Compared with traditional methods, the proposed method can overcome the drawback of original features loss of the centralized mapped data in the feature subspace and can improve the accuracy of fault diagnosis. Experimental results are carried out on both the Tennessee Eastman benchmark process and a case study of aluminum electrolytic production process to verify the effectiveness of the proposed method.

Finally, in item 33) in the Appendix, a hidden Markov model based monitoring method is proposed, which can not only handle the multimodality of process data but also captures the mode switching restrictions. A two-step Viterbi algorithm is put forward for effective mode detection in the event of faults, and a reconstruction based fault isolation algorithm is developed to build the contribution plots. Application examples demonstrate the effectiveness of the proposed monitoring method.

At this point, our Editorial for the "Special Section on Data-Driven Control and Learning Systems" ends. The papers in this Special Section cover the latest achievements in both theoretical research and practical application in this field. We hope these papers will provide new enthusiasm for scientists and researchers in this area, as well as for those who work in the practical system applications of the DDC and learning systems.

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ACKNOWLEDGMENT

The Guest Editors would like to thank all the authors who submitted their valuable work to this Special Section and the reviewers for their timely and insightful reviews that have greatly helped improve the quality of the papers published here. In addition, the Guest Editor appreciate the Editor-in-Chief of the IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, Prof. L. Franquelo, for accepting our proposal and providing his professional guidance in every stage of this Special Section. Finally, warm thanks are also extended to the Journal Administrators, Dr. R. Roman and Mrs. S. McLain, for their excellent support for the publication of this Special Section.

APPENDIX
RELATED WORK

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