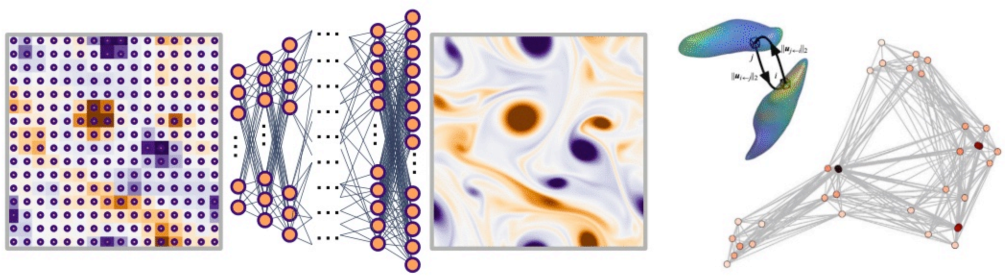
3rd Workshop on Data-Driven Fluid Dynamics



March 17-19, 2025
JR Gate Tower Conference, Nagoya, Japan

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Objectives:

There has been explosive growth in the applications of data-driven techniques to study a wide range of challenging problems in fluid dynamics over the last few years. Along with the advancement of computational, experimental, and theoretical approaches, the rapid development of data-driven analyses for flows that exhibit complex dynamics. Following the success of the past two US-Japan data-driven fluid dynamics workshops in 2018 (Tokyo) and 2022 (Kobe), we are opening this 3rd workshop to the international research community to promote discussions and potential collaborations across the world. This 3rd workshop will be held from March 17 to 19, 2025 at the JR Gate Tower Conference, Nagoya in Japan with approximately 60 invitation-only stakeholders in data-driven fluid dynamics from the academia, industry, and government. The objective of the workshop is to survey the state-of-the-art data-driven analysis techniques for fluid dynamics and discuss possibilities for breakthroughs by the community to advance data-driven analysis for a range of fluid dynamics problems.

Target Areas:

Data-inspired fluid dynamics, including but not limited to data-driven analysis, modeling, estimation, and control of fluid flows.

Sponsors:

We thank the generous support from

Asian Office of Aerospace Research and Development
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Organizers:

Kunihiko Taira (UCLA, Chair)
Taku Nonomura (Nagoya University)
Kai Fukami (Tohoku University)
Kozo Fujii (Tokyo University of Science)
Koji Fukagata (Keio University)
Steven Brunton (University of Washington)
Maziar Hemati (University of Minnesota)

Local Support Members:

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Takayuki Nagata (Nagoya University)
Naotaka Shigeta (Nagoya University)
Shunta Takahashi (Nagoya University)
Masahito Watanabe (Nagoya University)

Attendees (*Presenters)

Byungjin An* (Ebara)
Katherine Asztalos* (Argonne National Laboratory)
Shervin Bagheri* (KTH)
Steven Brunton* (University of Washington)
Szuyung Chen (Ebara)
Paola Cinnella* (Sorbonne Universite) - **keynote speaker**
Tim Colonius* (Caltech)
Jeff Eldredge* (UCLA)
Kozo Fujii (Tokyo University of Science)
Koji Fukagata* (Keio University)
Kai Fukami* (Tohoku University)
Kohei Fukunaga (Sumitomo Rubber Industries)
Susumu Goto* (Osaka University) - **keynote speaker**
Yosuke Hasegawa* (University of Tokyo)
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Kenta Inada* (Honda Motor Co)
Izuru Kambayashi (Ebara)
Soshi Kawai* (Tohoku University)
Adrián Lozano-Durán* (Caltech) - **keynote speaker**
Luca Magri* (Imperial College London)
Karen Mulleners* (EPFL)
Hiroya Nakao* (Institute of Science Tokyo)
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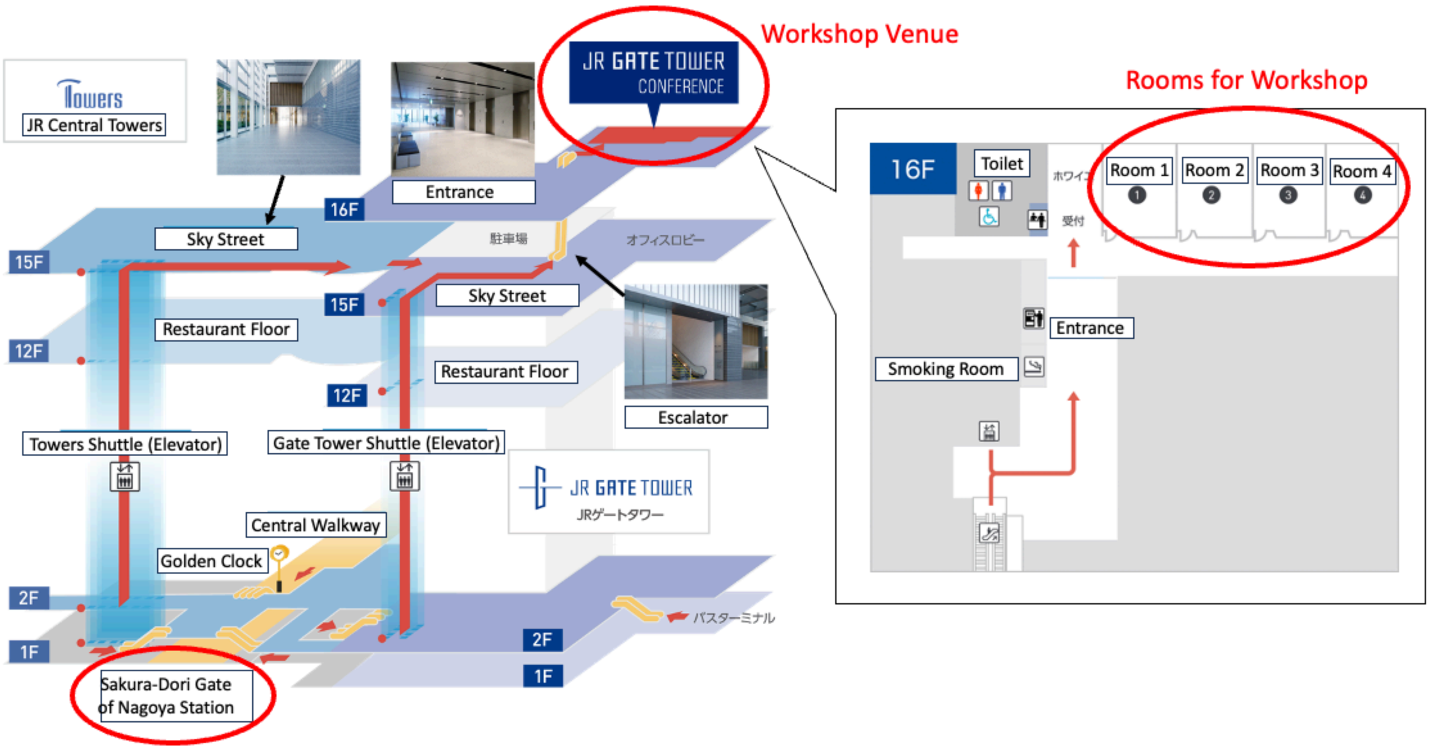
Ricardo Vinuesa* (KTH)
Heng Xiao* (University of Stuttgart)
Koichiro Yawata (Hitachi)
Donghyun You* (Pohang University of Science and Technology)

Map to the Conference Venue

Reference: JR Gate Tower Conference Website
https://www.towers.jp/jrgt-conference/access.php



Updated: March 13, 2025

SCHEDULE

DAY 1 (Monday, March 17, 2025)

REGISTRATION

9:00-9:20 **REGISTRATION AND COFFEE**

WELCOMING REMARKS

9:20-9:30 **Kunihiko Taira (UCLA)**

KEYNOTE TALK (Chair: Kunihiko Taira, UCLA)

9:30-10:10 **Susumu Goto (Osaka University)**
Machine-learning based turbulence models

10:10-10:20 **COFFEE BREAK**

SESSION I (Chair: Kai Fukami, Tohoku University)

10:20-10:40 **Soshi Kawai (Tohoku University)**
Unsupervised machine learning for SGS modeling in very coarse-grid LES

10:40-11:00 **Heng Xiao (University of Stuttgart)**
Towards a unified turbulence through multi-objective learning

11:00-11:20 **Isabel Scherl (University of Massachusetts)**
Ensemble Kalman Methods for Learning RANS Closure

11:20-11:40 **Shervin Bagheri (KTH)**
Solving the roughness problem using modeling and data-driven approaches

11:40-1:30 **LUNCH (provided)**

SESSION II (Chair: Koji Fukagata, Keio University)

1:30-1:50 **Ricardo Vinuesa (KTH)**
Turbulence control through explainable deep learning

1:50-2:10 **Yosuke Hasegawa (University of Tokyo)**
Turbulence control by combining machine learning and optimal control theory

2:10-2:30 **Kie Okabayashi (Osaka University)**
Optimization of fluid control laws through deep reinforcement learning using dynamic mode decomposition as the environment

2:30-2:50 **Taku Nonomura (Nagoya University)**
Data-driven real-time feedback control of flow behind cylinder by sparse processing particle image velocimetry and plasma actuator

2:50-3:10 COFFEE BREAK

SESSION III (Chair: Kie Okabayashi, Osaka University)

3:10-3:30 **Tim Colonius (Caltech)**
Data-driven modeling of coherent structures in forced turbulent flows

3:30-3:50 **Oliver Schmidt (UCSD)**
Spectral Modal Decomposition for Physical Discovery and Model Reduction

3:50-4:10 **Yuya Ohmichi (JAXA)**
Variational mode decomposition-based algorithm for extracting nonstationary coherent structures

4:10-4:30 **Hiroya Nakao (Institute of Science Tokyo)**
Phase-amplitude reduction approach for synchronization control of spatiotemporal rhythmic systems

4:30-4:50 **Kunihiko Taira (UCLA)**
Transient Flow Analysis and Control through Phase in Latent Space

4:50-5:00 BREAK

PANEL DISCUSSION I (Moderator: Kunihiko Taira, UCLA)

5:00-5:40 **Novel insights from machine learning beyond traditional analysis**
Panelists: **Tim Colonius (Caltech)**
Susumu Goto (Osaka University)
Luca Magri (Imperial College London)
Ricardo Vinuesa (KTH)

5:40-6:00 BREAK

6:00-8:00 BANQUET (at Conference Venue)

DAY 2 (Tuesday, March 18, 2025)

REGISTRATION

9:00-9:20	**REGISTRATION AND COFFEE**

KEYNOTE TALK (Chair: Kai Fukami, Tohoku University)

9:20-10:00	**Paola Cinnella (Sorbonne Universite)** Bayesian machine learning for fluid dynamic design

SESSION IV (Chair: Tim Colonius, Caltech)

10:00-10:20	**Luca Magri (Imperial College London)** Modelling unknown unknows for real-time digital twins
10:20-10:40	**Karen Mulleners (EPFL)** How to get smarter and in shape overnight with self-exploring automated experiments
10:40-11:00	**Gianluca Iaccarino (Stanford University)** Learning from Data vs. Data for Learning
11:00-11:20	**COFFEE BREAK**

SESSION V (Chair: Taku Nonomura, Nagoya University)

11:20-11:40	**Kai Fukami (Tohoku University)** Identifying interpolatory and extrapolatory vortical structures of data-driven fluid dynamics
11:40-12:00	**Ryo Onishi (Insitute of Science Tokyo)** Super-Resolution Simulation for Real-Time Prediction of Urban Micro-Meteorology
12:00-12:20	**Jeff Eldredge (UCLA)** Data-driven stochastic estimation and control of disturbed aerodynamic flows
12:20-12:40	**Koji Fukagata (Keio University)** Flow field reconstruction using floating sensors

12:40-2:00 **LUNCH (provided)**

2:00 **Excursion**

TOUR OF NAGOYA CASTLE

Depart the conference site at 2:00. Detailed schedule will be shared at the workshop.

DAY 3 (Wednesday, March 19, 2025)

REGISTRATION

9:00-9:20 **REGISTRATION AND COFFEE**

KEYNOTE TALK (Chair: Taku Nonomura, Nagoya University)

9:20-10:00 **Adrián Lozano-Durán (Caltech)**
Building-block flow model: An ML-based general-purpose closure model for LES

10:00-10:20 **COFFEE BREAK**

SESSION VI (Chair: Kunihiko Taira, UCLA)

10:20-10:40 **Donghyun You (POSTECH)**
Optimal CFD and design of a blade passage using deep reinforcement learning

10:40-11:00 **Georgios Rigas (Imperial College London)**
Reinforcement learning for road vehicle drag reduction in turbulent wind tunnel environments

11:00-11:20 **Kenta Inada (Honda Motor Co., Ltd.)**
Aerodynamic Drag Reduction Through Data-Driven Low-Dimensional Models

11:20-11:40 **Byungjin An (Ebara Corporation)**
Data Science Applications in Pumps

11:40-12:00 **Katherine Asztalos (Argonne National Laboratory)**
A Data-Driven Machine Learning Framework for Aerodynamic Analysis of Electrified, Hybrid, and Hydrogen Aircraft

12:00-12:20 **Steven Brunton (University of Washington)**

Machine Learning for Applied Engineering: Examples of Collaboration with Industry

PANEL DISCUSSION II (Moderator: Steven Brunton, University of Washington)

12:20-1:00 **Machine learning in applications and industry**
Panelists: **Katherine Asztalos (Argonne National Laboratory)**
Szuyung Chen (Ebara)
Gianluca Iaccarino (Stanford University)
Soshi Kawai (Tohoku University)

CLOSING REMARKS

1:00-1:10 **Kunihiko Taira (UCLA)**

1:10 **LUNCH (provided)**

Abstracts

KEYNOTE TALKS (30 minutes + 10 minutes Q&A)

Paola Cinnella (Sorbonne Universite)

Bayesian machine learning for fluid dynamic design

Many applications in the aerospace and energy sectors rely on the numerical solution of the Reynolds-averaged Navier-Stokes equations (RANS), supplemented with a turbulence model. Robust and relatively inexpensive, they nevertheless suffer from a number of shortcomings that limit their application to complex flows. Furthermore, these methods are ill-suited to describing so-called 'transitional' flows, in which laminar and turbulent zones co-exist. Recent advances in numerical methods for fluid mechanics, high-performance scientific computing and machine learning are opening up new opportunities. On one hand, high-fidelity approaches, such as direct numerical simulation or large-scale simulation of flows, are delivering large quantities of high-fidelity data to improve our understanding of physical phenomena. On the other hand, data-driven methods and machine learning are providing new tools for extracting information from these databases and for improving models, or for fusing data characterized by various levels of fidelity into efficient flow emulators with improved accuracy. However, several criticalities must be addressed for ML-enhanced CFD scaling-up to large problems of Engineering interest, including the limited availability of diverse high-fidelity databases, the lack of interpretability and generalization to out-of-distribution environments, and the need for quantifying predictive uncertainties. In my talk, I will adopt the point of view of Bayesian machine learning. Such a framework is well-suited for scarce/noisy data, it enables simultaneous model selection and inference, and it provides estimates of uncertainty in the predicted model outputs, a critical information in view of the robust design of energy conversion machines. Examples are shown for canonical flows and turbomachinery applications.

Susumu Goto (Osaka University)

Machine-learning based turbulence models

Turbulence is composed of eddies of various sizes. Since only large-scale flow is important for many transport phenomena, it would be good to construct a model closed only on large scales. In turbulent flow, on the other hand, energy, and thus information, are transferred from large to small scales. Therefore, small-scale motion should be predictable from large-scale motion. In this talk, we report our recent two studies using recurrent neural networks to construct turbulence models closed only with large-scale modes. The first is a foundational study using a shell model of turbulence that shows a qualitative difference in whether the cut-off scale is in the inertial or dissipative range. The second is a study on turbulence model when a cut-off scale is placed on a sufficiently large scale, i.e., in the energy-containing range, which cannot be handled by ordinary large eddy simulations. We show that not only spatial coarse-graining but also temporal coarse-graining is essential in such a model. In addition, we would like to mention some future prospects for turbulence modeling using machine learning.

Adrián Lozano-Durán (Caltech)

Building-block flow model: An ML-based general-purpose closure model for LES

The predictive capabilities of computational fluid dynamics, which are critical for aerodynamic design, depend on the development of accurate closure models. However, no practical model has emerged as universally applicable across the wide range of flow regimes relevant to the industry. We introduce a closure model for large-eddy simulation, referred to as the Building-block Flow Model (BFM). This model is founded on the premise that a finite set of simple flows encapsulates the essential physics required to predict more complex scenarios. The BFM is implemented using artificial neural networks and introduces five unique advancements within the large-eddy simulation framework: (1) It is designed to predict multiple flow regimes, including laminar flow, wall turbulence under zero, favorable, and adverse mean-pressure gradients, separation, wall heat transfer, and wall roughness effects; (2) It leverages information-theoretic dimensional analysis to select the most relevant non-dimensional input/output variables; (3) It ensures consistency with numerical schemes and gridding strategies by accounting for numerical errors; (4) It is directly applicable to arbitrary complex geometries; and (5) It is scalable for future extensions to model additional flow physics (e.g., laminar-to-turbulent transition). The BFM is utilized to predict key quantities of interest across a wide range of cases, such as turbulent pipes, turbine blades with roughness, speed bumps, aircraft in landing configurations, and hypersonic flows in entry, descent, and landing vehicles.

REGULAR TALKS (15 minutes + 5 minutes Q&A)

Byungjin An (Ebara Corporation)

Data Science Applications in Pumps

The irregular motion of eddies characterized by various spatiotemporal scales in turbulent flow is a primary cause of energy loss, vibrations, and noise. Therefore, the development of effective turbulence control technologies is crucial for enhancing fluid machinery performance and functionality. For pumps, which are representative fluid machinery, technologies for performance enhancement and reduction of vibrations and noise are crucial, driven by trends in miniaturization and higher rotation speed. Therefore, accurately identifying the sources of vibrations and noise, as well as developing suppression technologies, is essential for enhancing product value. To address this challenge, traditional approaches such as theoretical analysis, experiments, and numerical simulations have been carried out. Recent efforts have increasingly focused on the application of data science techniques. In this presentation, we introduce examples of new approaches to applying data science in pump research and development.

Katherine Asztalos (Argonne National Laboratory)

A Data-Driven Machine Learning Framework for Aerodynamic Analysis of Electrified, Hybrid, and Hydrogen Aircraft

Motivated by the imperative to enhance efficiency within the aviation sector, the development of electric, hybrid, and hydrogen-powered aircraft necessitates significant redesigns to accommodate alternative propulsion systems. A primary challenge lies in the integration of specific energy storage, propulsion systems, and accessory technology into the aircraft wings, which requires significant modifications to conventional structures. The characterization of aerodynamic performance for these novel aircraft can be partially achieved through computational fluid dynamics (CFD) simulations, which serve as effective tools for evaluating aerodynamic performance. However, estimating the energy consumption of these aircraft types requires tools like Argonne's Aeronomie, which models aircraft-level performance and predicts energy consumption for specified flight paths. Direct interfacing with CFD is impractical due to its computational intensity. Consequently, we aim to develop data-driven machine learning models trained on aerodynamic data derived from targeted CFD campaigns for various airfoils to provide in-situ aerodynamic performance predictions. Future endeavors will focus on integrating Aeronomie with these data-driven surrogate models to enhance predictive capabilities for estimating the energy consumption profiles of electric, hybrid, and hydrogen-powered aircraft.

Shervin Bagheri (KTH)

Solving the roughness problem using modeling and data-driven approaches

One of the key challenges in engineering is the reliable full-scale prediction of drag in rough wall-bounded turbulent flows. The difficulty stems from the diversity of relevant roughness topographies and the high computational cost of determining drag using direct numerical simulations (DNS). In this talk, I will present different approaches that we have developed to simplify or bypass the reliance on DNS for drag prediction. These include mathematical and physical methods, such as inhomogeneous boundary conditions and quasi-linear models that incorporate nonlinearity through the mean flow. It also includes data-driven techniques for drag prediction (support-vector machines and neural networks), focusing on achieving a balance between predictive accuracy and generalizability. Finally, I will discuss some of our attempts to use these prediction techniques to gain new insights into the physics of roughness and turbulence.

Steven Brunton (University of Washington)

Machine Learning for Applied Engineering: Examples of Collaboration with Industry

This talk will describe how to leverage machine learning to solve canonically hard problems in engineering, specifically in the domains of fluid dynamics and manufacturing. First we will discuss how machine learning can be used to extract dominant patterns from high-dimensional data. Next, we will explore how machine learning optimizations can be used to learn interpretable and generalizable dynamical systems models by promoting sparsity to uncover key physical mechanisms. These techniques are also used to learn effective sensor and actuator placements and nonlinear control laws. Finally, working with Boeing, we have developed sparse optimization technologies that are currently in production on the 737, 787, and 777 manufacturing lines, with projected savings in the hundreds of millions of dollars.

Tim Colonius (Caltech)

Data-driven modeling of coherent structures in forced turbulent flows

The spectral proper orthogonal decomposition (SPOD) and resolvent analysis provide a compelling framework for modeling coherent structures in turbulent flows. We review the application of these tools to analyze and model turbulence in free-shear and wall-bounded turbulence, including efforts to model the nonlinear resolvent forcing using data-driven approaches. We also discuss our recent extension of SPOD/resolvent frameworks to time-periodic and quasi-periodic turbulent flows using cyclo-stationary statistical analysis.

Jeff Eldredge (UCLA)

Data-driven stochastic estimation and control of disturbed aerodynamic flows

There is a wide variety of applications in which we may need knowledge of a transient fluid flow, but we only have information from a few noisy sensors. For example, small flight vehicles, targeted for many emerging applications, are more agile but also more strongly affected by unexpected disturbances ('gusts') than larger vehicles. Any flow control strategy for such a vehicle is generally more effective if it can rely on an estimation of the vehicle's current flow state from available sensors. In this talk, I will discuss the dynamic estimation and uncertainty quantification of flows from limited sensor data and the control of the flow with deep learning strategies. I will first discuss aspects of the flow estimation problem within the context of Bayesian inference and ensemble Kalman filters, which allow us to easily combine physics-based and/or data-driven models of the flow with measurement data from sensors. The assimilation of these measurements can compensate for the physics that are unrepresented in the model. In the examples I will show, we use the estimation framework to predict the fluid dynamics of a separated aerodynamic flow subjected to a gust, relying on the surface pressure measurements to inform the model of the gust. Then, I will discuss the use of deep reinforcement learning to develop strategies for the mitigation of gust encounters, based on available sensor data.

Koji Fukagata (Keio University)

Flow field reconstruction using floating sensors

We introduce our recent attempt on estimations of flow fields using only floating sensor locations [Oura, Miura, and Fukagata, arXiv:2311.08754v2]. This method does not require either ground-truth velocity fields or governing equations for fluid flows. The machine learning model is supposed to generate accurate velocity fields so that the time variation of sensor motion is consistent with the given data of sensor locations. The performance of the proposed method is assessed using a two-dimensional forced homogeneous isotropic turbulence and a two-dimensional ocean current field, which demonstrates the accuracy and the practicality of this method. Moreover, we observe that the present method can estimate the major structures, such as coherent structures in the forced turbulence and stable ocean currents, with only a few sensors.

Kai Fukami (Tohoku University)

Identifying interpolatory and extrapolatory vortical structures of data-driven fluid dynamics

This talk considers the questions of when machine learning works/fails of data-driven analyses for unsteady flows. The question raised here is often translated with a problem of inter- (seen) and extrapolation (unseen) scenarios in data science. However, categorizing seen and unseen vortical structures is generally not clear-cut, especially for modern machine-learning techniques that accommodate translational and rotational invariances. We show that a Buckingham-Pi sparse regression on a coordinate composed of the second and third invariants identifies inter- and extrapolatory vortical structures. This enables the assessment of possible high-risk extrapolations, demonstrated with the super-resolution analysis that reconstructs a high-resolution flow field from low-resolution data. Based on the finding above, we further argue that each of turbulent flow snapshots can hold more information than a single data file in general machine-learning settings. We introduce our recent study exhibiting that turbulence super-resolution can be accurately performed by cleverly subsampling data from only a single snapshot. These findings provide guidance on how we should incorporate prior knowledge of flow physics in designing machine-learning models and collecting turbulent flow data.

Yosuke Hasegawa (University of Tokyo)

Turbulence control by combining machine learning and optimal control theory

The present study proposes new strategies for combining two different approaches for flow control, i.e., optimal control theory and machine learning. Optimal control theory is a well-established approach to optimize control variables with large degrees of freedom to minimize a prescribed cost functional. Meanwhile, setting a proper cost functional is not so trivial, and has relied on trials-and-errors. In the present study, we leverage machine learning techniques to automatically search for effective cost functions. It will be demonstrated that our framework successfully finds novel cost functionals as well as existing ones reported in the literatures.

Gianluca Iaccarino (Stanford University)

Learning from Data vs. Data for Learning

Data-driven modeling techniques have achieved success in a broad spectrum of applications, including automotive aerodynamics. Extensive research efforts are devoted to enhance the accuracy and robustness of statistical learning approaches starting from existing datasets (e.g. shapenet, blastnet) within the paradigm of "learning from data”. Conversely, limited attention is being devoted to the principles that make datasets well suited for learning especially for realistic industrial applications. Many existing data collections suffer from a lack of quantification of intrinsic properties (such as coverage and diversity) that correlate with predictive performance of data-driven approaches on unseen samples, focusing almost exclusively on size (number of samples). Although it is true that the amount of data available is an important metric, it is obvious that highly correlated and clustered data is synonym of poor generalization properties. In this work, a database construction strategy is proposed that allows for the controlled generation of an arbitrary number of samples, by convex interpolation between a small number of basis cases. This synthetic construction enables a precise dataset characterization based on size and data clustering (or density). Furthermore, formal measures of diversity of a given dataset are developed. This approach is independent of the statistical learning strategy employed and focuses on the ideal "data for learning". We demonstrate this data-construction approach on problems related to vehicle aerodynamics where the space of possible shapes is extremely high-dimensional and often does not enable a consistent parametrization. We develop multiple datasets that have fixed size, but varying diversity and coverage and illustrate how the training of different machine learning algorithms is affected. We demonstrate that a priori measures of dataset diversity correlate well with prediction accuracy for unseen cases.

Kenta Inada (Honda Motor Co., Ltd.)

Automotive Aerodynamic Drag Reduction Through Data-Driven Low-Dimensional Models

Emission regulations are becoming more stringent, as global temperature continues to rise due to the increasing greenhouse gases in the atmosphere. Battery electric vehicles (BEV) are expected to become widespread to solve this problem. As the powertrain of BEV is more efficient than conventional powered vehicles, the proportion of energy loss during driving due to aerodynamic drag becomes greater. Therefore, reducing aerodynamic drag for improved energy efficiency is important to extend the pure electric range. Current methods to reducing aerodynamic drag involve examining a high dimensional parameter space of different geometric configurations through costly computational calculation and wind tunnel experiments. This naturally calls for data-driven approaches to generate lower-cost, efficient surrogate aerodynamic models to expedite the vehicle design cycle. We constructed an autoencoder that can predict drag coefficient and flow fields from automobile geometries. By combining POD with the input/output of the autoencoder, memory usage during training is significantly reduced. We show that a relationship between these automobile geometries and their respective drag coefficient can be extracted in a low-dimensional manner by leveraging a POD assisted autoencoder which is simultaneously trained to produce automobile geometries and estimate of the drag coefficient from the latent variables. By using the local gradient of the drag coefficient for latent variables, automobile geometry with reduced drag coefficient is generated. The findings of this work serve as a foundation for the application of data-driven approaches to the analysis and design of vehicles.

Soshi Kawai (Tohoku University)

Unsupervised machine learning for SGS modeling in very coarse-grid LES

In recent years, scale-resolving methods, such as LES, have not only been used for academic research but have also increased attention in the industry. The most significant limitation of the LES for practical use is its high computational cost, which originates from the fundamental requirement of resolving the energetic turbulent eddies in the LES. In this talk, we try to alleviate this limitation by using unsupervised machine learning to construct the super-resolution-based SGS model in very coarse-grid LES that does not resolve the energetic eddies, i.e., considering the situation that violates the LES requirement. Unlike typical super-resolution, unsupervised machine learning (CycleGAN in this study) is indispensable for very coarse-grid LES modeling. Interestingly, a significant amount of SGS backscatter is predicted by machine learning, and we found that the predicted SGS backscatter plays a crucial role in the very coarse-grid LES.

Luca Magri (Imperial College London, The Alan Turing Institute, Politecnico di Torino)

Modelling unknown unknows for real-time digital twins

Low-order models, derived by physical assumptions and numerical approximations, are prone to uncertainties in state, parameters, and model biases. Model biases—systematic errors that are 'unknown unknowns'—are difficult to infer due to their undefined functional form. Data assimilation methods for biased models may be ill-posed as they either (i) assume unbiased estimators, (ii) rely on predefined parametric models for bias, or (iii) yield non-unique bias estimates. To address this, we develop a data assimilation framework for simultaneous state, parameter, and bias estimation. Our approach employs the regularized bias-aware ensemble Kalman Filter (r-EnKF), which requires a bias model and its Jacobian. We use an echo state network for bias estimation, derive its Jacobian, and implement a robust training strategy with data augmentation for improved accuracy. This enables real-time and simultaneous inference of parameters, states, and a unique bias. We apply this framework to develop a real-time digital twin of a hydrogen-based annular combustor by integrating a physics-based low-order model with sparse experimental microphone data. Using the bias-regularized ensemble Kalman filter and a reservoir computer, the digital twin autonomously predicts azimuthal acoustic dynamics, extracts physical acoustic pressure from noisy data, and generalizes across different scenarios. This enables more accurate and adaptable real-time thermoacoustic modeling, opening new possibilities for multi-physics digital twinning.

Karen Mulleners (EPFL)

How to get smarter and in shape overnight with self-exploring automated experiments

Leaves, insect wings, and fish fins are only a few examples of flexible structures found in nature that come in a myriad of different shapes and sizes, which might affect the way they interact with the surrounding flow. This idea inspired us to study how the planform shape of cantilevered flexible sheets or flags affect their flapping dynamics, critical flutter velocity, and the aerodynamic forces they experience. The shape design space of such flags is vast, and only a selected number of shapes could be tested using conventional supervised experiments. To cover and explore a larger portion of the input parameter space, we are developing a self-exploring automated experiment using (industrial) robots that can continuously and in loop fabricate flags with different planform shapes, measure their structural and aerodynamic response, analyse the fluid-structure interactions, and select new flag shapes to test. To optimise and guide the selection of the new flag shapes, we are combining different data-science tools that can help us maximise the information gain with every new experiment and drive exploration to uncover new flapping regimes. This self-exploring automated experimental approach will allow us to increase experimental throughput and expedite scientific discovery.

Hiroya Nakao (Institute of Science Tokyo)

Phase-amplitude reduction approach for synchronization control of spatiotemporal rhythmic systems

Dynamical reduction is a useful approach for analyzing and controlling nonlinear dynamical systems. Recent studies have clarified the relationship between the phase reduction method for nonlinear oscillators and the Koopman operator theory, leading to the generalization of the classical phase reduction method to the phase-amplitude reduction method. This generalized method can describe not only the phase but also the amplitude deviations of the system state with respect to the periodic trajectory. In this talk, applications of the phase-amplitude reduction method to synchronization dynamics of nonlinear oscillatory systems will be presented, including the analysis of spatiotemporal rhythmic systems and data-driven approaches to synchronization control.

Taku Nonomura (Nagoya University)

Data-driven real-time feedback control of flow behind cylinder by sparse processing particle image velocimetry and plasma actuator

In this presentation, real-time feedback control of asymmetricity of flow behind cylinder by sparse processing particle image velocimetry (SPPIV) and a plasma actuator is presented. Here, SPPIV is a real-time PIV technique that reconstruct the entire flow fields based on results of PIV on a limited number of sparse optimized processing interrogation window and spatial POD mode distribution. Since a plasma actuator is responding immediately but does not give sufficient induced flow, on-off control with the maximum voltage should be employed. For this purpose, flow control law is calculated using sum-of-absolute-value control law and solved by proximal splitting algorithms in real time. The techniques above allows us to successfully conduct the real time flow control. The results show that the asymmetricity of flow behind cylinder is suppressed to some extent.

Kie Okabayashi (Osaka University)

Optimization of fluid control laws through deep reinforcement learning using dynamic mode decomposition as the environment

The optimization of fluid control laws through deep reinforcement learning (DRL) presents a challenge owing to the considerable computational costs associated with trial-and-error processes. In this study, we examine the feasibility of deriving an effective control law using a reduced-order model constructed by dynamic mode decomposition with control (DMDc). DMDc is a method of modal analysis of a flow field that incorporates external inputs, and we utilize it to represent the time development of flow in the DRL environment. We also examine the amount of computation time saved by this method. We adopt the optimization problem of the control law for managing lift fluctuations caused by the Kármán vortex shedding in the flow around a cylinder. The deep deterministic policy gradient is used as the DRL algorithm. The external input for the DMDc model consists of a superposition of the chirp signal, containing various amplitudes and frequencies, and random noise. This combination is used to express random actions during the exploration phase. With DRL in a DMDc environment, a control law that exceeds the performance of conventional mathematical control is derived, although the learning is unstable (not converged). This lack of convergence is also observed with DRL in a computational fluid dynamics (CFD) environment. However, when the number of learning epochs is the same, a superior control law is obtained with DRL in a DMDc environment. This outcome could be attributed to the DMDc representation of the flow field, which tends to smooth out high-frequency fluctuations even when subjected to signals of larger amplitude. In addition, using DMDc results in a computation time savings of up to a factor of 3 compared to using CFD.

Yuya Ohmichi (JAXA)

Variational mode decomposition-based algorithm for extracting nonstationary coherent structures

We introduce a novel spatiotemporal pattern analysis method called VMD-based Nonstationary Coherent Structure (VMD-NCS) analysis for extracting and analyzing coherent structures from fluid flow data. This technique combines proper orthogonal decomposition (POD) for dimensionality reduction with multivariate variational mode decomposition (MVMD) to effectively process nonstationary phenomena such as nonperiodic or intermittent events. A feature of VMD-NCS is that it decomposes input data into intrinsic coherent structures (ICSs) which can represent nonstationary behaviors, including nonperiodic fluctuations and nonlinear amplitude growth, while maintaining coherence in both spatial and temporal directions. The method also effectively mitigates the frequency mixing issues often encountered in conventional POD analyses, enabling separation of different frequency components. The effectiveness of this method will be demonstrated through its application to the analysis of transonic buffet phenomena.

Ryo Onishi (Institute of Science Tokyo)

Super-Resolution Simulation for Real-Time Prediction of Urban Micro-Meteorology

We, as human about one-meter in height, live in meter-order micro-meteorology, i.e., micro-weather scales, rather than the broader, kilometer-order weather systems. Realization of real-time prediction of micro-meteorology is a key of future smart services, such as drone logistics, smart energy and so on. However, one major challenge in realizing the prediction is the computational bottleneck: micro-meteorolgy simulations cannot be completed promptly enough to be useful in real-time applications. Here we present a novel technology that combines machine-learning (ML) and physics simulation technologies to solve the bottleneck, enabling real-time micro-meteorology simulations. Our team has proposed the super-resolution (SR) simulation, which merges a deep neural network for SR with a physics-based meteorological simulation. My talk will introduce the advancements in this SR technology in meteorological research.

Georgios Rigas (Imperial College London)

Reinforcement learning for road vehicle drag reduction in turbulent wind tunnel environments

The complex wake dynamics behind road vehicles are a major contributor to aerodynamic drag, posing significant challenges to energy efficiency. This study highlights recent advancements by our group in developing dynamic closed-loop control schemes to optimise the aerodynamic performance of 3D road vehicles in turbulent regimes. As a starting point, we deploy Reinforcement Learning (RL) within digital environments (specifically Direct Numerical Simulations), to demonstrate that dynamic rear flaps can fully stabilise vortex shedding instabilities in laminar regimes using feedback from only body-mounted pressure sensors. Building on these results, we extend our approach to heavy road vehicle models operating in turbulent conditions, conducting experiments in the 10x5 National Wind Tunnel Facility. In these experiments, we establish a real-time, time-critical control loop to enable seamless interactions between the RL controllers and the flow environment. The RL controller, trained directly using experimental data, processes immediate feedback from surface-mounted pressure sensors on the truck, generating control signals to adjust motorised rear pitching flaps. Key challenges include managing the highly turbulent wake, mitigating the effects of partial observability caused by limited sensor data, and addressing signal delays. To tackle these, we incorporate memory-based neural networks and advanced RL algorithms. Our results demonstrate a significant reduction in wake instabilities, underscoring the potential of RL-driven dynamic control to enhance aerodynamic efficiency in real-world applications. This work is supported by the UKRI AI for Net Zero grant (EP/Y005619/1). https://www.imperial.ac.uk/ai-net-zero/

Isabel Scherl (University of Massachusetts, Amherst)

Ensemble Kalman Methods for Learning RANS Closure

Reynolds-averaged Navier-Stokes (RANS) simulations rely on closure models to approximate Reynolds stresses. These closures often contain parameters that can be adjusted to fit the system being modeled. Estimating parameters is essential for implementing accurate and effective closure models. We demonstrate how techniques in data assimilation can be used to determine the optimal values of these parameters. The test case in this work is the minimal flow unit, a channel simulation that is considered to be the smallest domain to sustain turbulent structures. As such, it has become a common test case for algorithmic development. Recent efforts have shown that ensemble Kalman methods can accurately and efficiently estimate system states. These techniques typically utilize observations and an ensemble of model realizations. In this work, ensemble Kalman inversion (EKI), a method that was developed to iteratively optimize model parameters, is used to build a

Reynold stress closure. Preliminary results show that the closure EKI converges on produces accurate statistics.

Oliver Schmidt (UCSD)

Spectral Modal Decomposition for Physical Discovery and Model Reduction

Modal decomposition techniques are at the forefront of scientific discovery from large experimental and numerical datasets of complex engineering and natural flows. While we briefly discuss classical methods such as space-only proper orthogonal decomposition (POD) and dynamic mode decomposition (DMD), the focus is on spectral modal decomposition techniques, with spectral proper orthogonal decomposition (SPOD) being the most widely used. As an empirical approach rooted in spectral estimation, SPOD yields convergent modal bases even for high Reynolds number turbulent flows. Alongside other operator- and data-driven decompositions, SPOD is now routinely employed for physical discovery from large flow datasets, providing a versatile framework for classification, reduced-order modeling, and flow control. While SPOD effectively identifies dominant spectral features, uncovering the underlying nonlinear dynamics and scale interactions requires incorporating the exact form of nonlinearity. To address this, we introduce triadic orthogonal decomposition (TOD), a novel method that identifies coherent structures optimally capturing spectral momentum transfer. TOD quantifies coupling and energy exchange through an energy budget bispectrum and highlights regions of triadic interaction. By distinguishing three essential components—momentum recipient, donor, and catalyst—TOD elucidates the laws governing pairwise, six-triad, and global triad conservation. The methods are demonstrated on diverse numerical and experimental datasets, providing a comprehensive framework for understanding spectral dynamics and reducing the complexity of nonlinear fluid flows.

Kunihiko Taira (UCLA)

Transient Flow Analysis and Control through Phase in Latent Space

Phase is generally associated with oscillatory dynamics. Here, we extend the concept of phase to the analysis and control of transient flow dynamics. This can be achieved by expressing the transient flow evolution on a manifold identified through a nonlinear autoencoder with appropriate physics embedded. By tracking the transient dynamics on a manifold, we are able to capture the essence of nonlinear flow dynamics and characterize their response to flow control input. This is critically important for enabling flow modification on a fast time scale. In this talk, we demonstrate these concepts with extreme aerodynamic flow examples where wings are bombarded with strong gust vortices. In these examples, machine learning methods take advantage of the topological features in the data such that we can examine the flow physics in latent space using phase based on a flow event-based metric.

Ricardo Vinuesa (KTH)

Turbulence control through explainable deep learning

In this presentation we first use a framework for deep-learning explainability to identify the most important Reynolds-stress (Q) events in a turbulent channel (simulated via DNS) and a turbulent boundary layer (obtained experimentally). This objective way to assess importance reveals that the most important Q events are not the ones with the highest Reynolds shear stress. This framework is also used to identify completely new coherent structures, and we find that the most important coherent regions in the flow only have an overlap of 70% with the classical Q events. In the second part of the presentation we use deep reinforcement learning (DRL) to discover completely new strategies of active flow control. We show that DRL applied to a blowing-and-suction scheme significantly outperforms the classical opposition control in a turbulent channel: while the former yields 30% drag reduction, the latter only 20%. Then, we use different types of coherent structures to inform the reward of the DRL framework, finding much better results than simply using drag reduction as a reward. We conclude that DRL has tremendous potential for drag reduction in a wide range of complex turbulent-flow configurations.

Heng Xiao (University of Stuttgart)

Towards a unified turbulence through multi-objective learning

Existing data-driven turbulence models are often trained on datasets featuring a single flow mechanism, while industrial flows typically involve multiple coexisting mechanisms (e.g., free shear and wall-bounded flows). Developing a unified turbulence model capable of handling diverse regimes without manual zoning or blending remains a challenge. This work addresses this by training a unified model on heterogeneous datasets using multi-objective learning. The resulting model is tested on a wide range of flows, including secondary flows in square ducts, flow over periodic hills, and flow around airfoils.

Donghyun You (Pohang University of Science and Technology)

Optimal CFD and design of a blade passage using deep reinforcement learning

A deep-reinforcement-learning-(DRL)-based method for an optimal computational fluid dynamics (CFD) solution for a blade passage, yielding the highest simulation accuracy with minimal cost is introduced. Unlike traditional methods necessitating iterative tuning of meshing parameters for each new geometry and flow condition, the present method trains a mesh generator to efficiently determine optimal parameters across various configurations without iteration. Firstly, parameters controlling the mesh shape are optimized to maximize the geometric quality of a mesh, which is assessed through metrics including the min-max ratio of determinants of the Jacobian matrices and the cell skewness. Subsequently, resolution-controlling parameters are optimized by incorporating CFD results. Leveraging a multi-agent reinforcement learning technique, 256 agents concurrently construct meshes and conduct CFD analyses across randomly assigned flow configurations, striving for minimum simulation error and computational cost within a multi-objective optimization framework. After the training, the mesh generator reliably produces a mesh that yields a converged solution at desired computational costs for a new configuration in a single simulation, thereby eliminating the necessity for iterative CFD procedures for grid convergence. This method is extended to provide an optimal blade profile for efficiency using another DRL-based algorithm and the CFD data produced by the optimal CFD-DRL model.