EUROPEAN MECHANICS SOCIETY

Photo by Jerilee Cornelio on Unsplash, 2020.

Euromech Colloquium 614

Machine learning methods for prediction and control of turbulent flows

June 16-18, 2021
Paris, France

Chairpersons :

- **Dr. Lionel Mathelin**
- **Prof. Peter Schmid**
- **Prof. Bernd R. Noack**
- **Prof. Iraj Mortazavi**

Website : http://614.euromech.org

Euromech Colloquium 614

Machine learning methods for prediction and control of turbulent flows

June 16-18, 2021. Paris, France.

This is the short version of the booklet for print use. Full abstracts with all authors, references, and figures can be found in the electronic version at
`https://amcosconference.com/`

The open-source LaTeX template, AMCOS_booklet, used to generate this booklet is available at `https://github.com/maximelucas/AMCOS_booklet`

Contents

About

The **European Mechanics Society** is an international non-governmental non-profit scientific organization. The objective of the Society is to engage in all activities intended to promote in Europe the development of mechanics as a branch of science and engineering. The present colloquium is part of the **European Mechanics Society Colloquia series**.

Machine learning methods for prediction and control of turbulent flows

The steady rise of machine learning techniques, combined with the availability of affordable sensor arrays, has had a tranformative impact in a large number of scientific fields. With the dramatic increase in data accessibility and computational power, traditional model-based approaches in engineering are giving way to a data-enhanced paradigm. Prediction and control of turbulent flows, a challenging area of engineering sciences, are no exception in this respect. Despite early attempts, the successful control of such complex systems by machine learning techniques raises specific issues such as weak observability or an exhaustive range of temporal and spatial scales. Moreover, the effective incorporation of knowledge about the physical system, such as symmetries, invariances or conservation laws, into the learning process is far from trivial.

Nonetheless, recent success of machine learning techniques in the prediction of chaotic dynamical systems and control of highly nonlinear flows has fueled a great many research efforts and has shown that progress in this field critically relies on an interdisciplinary skill set, ranging from applied mathematics and machine learning to physics, from compute science to experimental methods. The aim of this workshop is thus to bring together control practitioners, fluid dynamicists and machine learning experts to critically review recent developments in the field and identify both opportunities and challenges in using machine learning techniques for high-dimensional physical systems. The workshop should act as a forum for exchanging ideas and as an occasion to learn and discuss.

Organizing committee

Lionel Mathelin (CNRS)
Bernd R. Noack (Harbin Institute of Technology)
Onofrio Semeraro (CNRS)
Jean-Christophe Loiseau (Arts & Métiers)
Peter J. Schmid (Imperial College)
Iraj Mortazavi (CNAM)
Michele Alessandro Bucci (INRIA)

Scientific committee

Michele Alessandro Bucci (INRIA)
Erik Bollt (Clarkson Univ.)
Karthik Duraisamy (U. Michigan)
Azeddine Kourta (Univ. Orléans)
Themis Sapsis (MIT)
Luca Biferale (Univ. of Rome)
Laurent Cordier (CNRS)
Angelo Iollo (INRIA)
Jean-Christophe Loiseau (Arts & Métiers)
Onofrio Semeraro (CNRS)

Timetable

CT: Contributed Talk, KL: Keynote Lecture.

Wednesday, 16 of June

8:50–9:00	**Welcome remarks**		
9:00–10:00	KL	**W. Zhang**	Machine learning for complex flow and flow active control
10:00–10:20	CT	**L. Magri, A. Racca and N. Doan**	Physics-aware reservoir computing for chaotic learning
10:20–10:40	CT	**M. Croci, U. Sengupta and M. Juniper**	Online parameter inference for the simulation of a Bunsen flame using heteroscedatic Bayesian neural networks ensembles
10:40–11:10	**Coffee**		
11:10–11:30	CT	**J. Yang, S. Lee, S. Bagheri, A. Stroh and P. Forooghi**	Towards and active learning-based model for prediction of roughness hydrodynamic properties
11:30–11:50	CT	**M. Frihat, M. Malhomme, B. Podvin, L. Mathelin, Y. Fraigneau and F. Yvon**	Unsupervised identification of motifs in turbulent flows using Latent Dirichlet Allocation
11:50–12:10	CT	**D. Carter, F. De Voogt and B. Ganapathisubramani**	Sparse reconstruction of flow over a stalled aerofoil using experimental data
12:10–12:30	CT	**A. Colon de Carvajal, P. Gilotte and I. Mortazavi**	Reduced order modeling for shear layer control over an inclined step
12:30–14:00	**Lunch**		
14:00–15:00	KL	**T. Sapsis**	TBA

15:00–15:20	CT	**S. Lee, J. Yang, P. Forooghi, A. Stroh and S. Bagheri**	A transfer learning framework to learn the Hama roughness function from a small dataset and empirical correlations
15:20–15:40	CT	**R. Semaan, D. Fernex and B. Noack**	Cluster-based network modeling of complex dynamical systems
15:40–16:10	**Coffee**		
16:10–16:30	CT	**T. Kiwitt, M. Meinke and W. Schröder**	Comparison of drag correlation functions for ellipsoidal particles derived theoretically and via genetic programming
16:30–16:50	CT	**A. Girayhan Özbay, A. Hamzehloo, S. Laizet, P. Tzirakis, G. Rizos and B. Schuller**	General-purpose neural 2D Poisson solver with applications to CFD
16:50–17:10	CT	**P. Baddoo, B. Herrmann, B. McKeon and S. Brunton**	Kernal learning for Robust Dynamic Mode Decomposition
17:10–17:30	CT	**E. Farzamnik, A. Ianiro, S. Discetti, N. Deng, B. Noack and V. Guerrero**	A manifold learner for wake flows: application to the fluidic pinball

Thursday, 17 of June

9:00–10:00	KL	**A. Iollo**	Parametrized flows: examples of convergence between data and computational science
10:00–10:20	CT	**G. Haller, S. Jain and M. Cenedese**	Nonlinear model reduction from equations and data to spectral submanifolds
10:20–10:40	CT	**B. Hug, E. Mémin and G. Tissot**	Koopman eigenfunctions estimation from reproducing kernel Hilbert space manifold and ensemble forecasts
10:40–11:00	**Coffee**		
11:00–11:20	CT	**N. Kumar, F. Kerhervé and L. Cordier**	Data-driven flow modelling using machine learning and data assimilation
11:20–11:40	CT	**N. Deng, B. Noack, M. Morzynski and L. Pastur**	Galerkin force model for transient and post-transient dynamics – exemplified for the fluidic pinball
11:40–12:00	CT	**E. Menier, M. A. Bucci, M. Yagoubi and M. Schoenauer**	Complementary deep-reduced order model
12:00–14:00	**Lunch**		
14:00–15:00	KL	**K. Duraisamy**	Infusing physical and numerical structure into Autoencoders for operator-theoretic decomposition and model reduction of spatio-temporal dynamics
15:00–15:20	CT	**R. Heinonen and P. Diamond**	Learning how structures form in drift-wave turbulence
15:20–15:40	CT	**L. Fery, B. Durbrulle, B. Podvin, F. Pons and D. Faranda**	Identification of sea level pressure anomaly patterns using Latent Dirichlet Allocation
15:40–16:10	**Coffee**		
16:10–16:30	CT	**J. McArt, J. Sirignano and J. Freund**	Learning subgrid-scale turbulence models: coupling back-propagation with adjoint flow equations
16:30–16:50	CT	**H. Bae and P. Koumoutsakos**	Multi-agent reinforcement learning of wall-modeled LES
16:50–17:10	CT	**D. Bezgin and N. Adams**	Neural ODES as PDF turbulence models

17:10–17:30	CT	**M. Buzzicotti, T. Li, F. Bonaccorso, P. Clark Di Leoni and L. Biferale**	Reconstruction of turbulent data with deep generative models for semantic inpainting from TURB-Rot database

Friday, 18 of June

9:00–10:00	KL	**L. Biferale**	Equation-informed and data-driven tools for Eulerian and Lagrangian turbulent problems
10:00–10:20	CT	**T. Guégan, M. A. Bucci, O. Semeraro, L. Cordier and L. Mathelin**	Closed-loop control of complex systems using deep Reinforcement Learning
10:20–10:40	CT	**P.Y. Passaggia, N. Mazellier and A. Kourta**	Experimental closed-loop control of an airfoil using linear genetic programming at high Reynolds numbers
10:40–11:10	**Coffee**		
11:10–11:30	CT	**Y. Li, Z. Yang, M. Morzynski, Z. Qiao, S. Krajnovic and B. Noack**	Explorative gradient method for multi-actuator flow control
11:30–11:50	CT	**G. Y. Cornejo Maceda, Y. Li, F. Lusseyran, M. Morzynski and B. Noack**	Gradient-based machine learning control exemplified for the stabilization of the fluid pinball and open cavity experiment
11:50–12:10	CT	**R. Paris, S. Beneddine and J. Dandois**	Deep reinforcement learning for nonlinear closed-loop flow control and sensor placement
12:10–14:00	**Lunch**		
14:00–14:20	CT	**A. Ferrero, F. Laracca, A. Iollo and T. Philibert**	Machine learning methods for the simulation of turbulent flows in turbomachinery
14:20–14:40	CT	**P. S. Volpiani, M. Meyer, L. Franceschini, J. Dandois, F. Renac, E. Martin, O. Marquet and D. Sipp**	Mahcine-learning augmented turbulence modeling for RANS simulations of flows over periodic hills
14:40–15:00	CT	**I. Ben Hassan Saïdi, P. Cinnella and F. Grasso**	Turbulence modeling using CFD-driven symbolic identification
15:00–15:20	CT	**A. Lozano-Durán and H. Bae**	Wall model for LES based on building-block flows
15:20–15:50	**Coffee**		

15:50–16:10	CT	**V. Srivastava and K. Duraisamy**	Developing generalizable data-driven model augmentations using learning and inference asssisted by feature-space engineering
16:10–16:30	CT	**K. Fukami and K. Taira**	Machine-learned invariant map for tubulent flow analysis and modeling
16:30–17:30	KL	**E. M. Bollt**	TBA
17:30	**Closing words**		

List of Abstracts – Talks

Due to LaTeX formatting issue, figures had to be stripped from the abstracts. We apologize for the inconvenience.

Wednesday 16th

Physics-aware reservoir computing for chaotic learning

L. Magri[1-4], A. Racca[4], and N. A. K. Doan[3, 5]

[1] Imperial College London, Aeronautics Dept., UK
[2] Alan Turing Institute, London, UK
[3] Institute for Advanced Study, TU Munich, Germany
[4] University of Cambridge, Engineering Dept., Cambridge, UK
[5] TU Delf, Aerospace Dept., the Netherlands

The ability of fluid mechanics modelling to predict the evolution of a flow is enabled by physical principles and empirical approaches. Physical principles, for example conservation laws, are extrapolative (until the assumptions upon which they hinge break down): they provide predictions on phenomena that have not been observed. Human beings are excellent at extrapolating knowledge because we are excellent at finding physical principles. Empirical modelling provides correlation functions within data. Artificial intelligence and machine learning are excellent at empirical modelling.

In this talk, the complementary capabilities of both approaches will be exploited to predict chaotic flows. The focus of the talk is on computational methodologies for learning dynamics of chaotic flows from data. Applications are aimed at hidden variable reconstruction, learning of long-term statistics from short-time data, filtering stochastic noise out of data to learn the deterministic structures, and time-accurate prediction of turbulence. Three physics-aware architectures are presented: physics-informed echo state networks (PI- ESN), automatic-differentiated physics-informed echo state networks (API-ESN), and auto-encoder echo state networks (AE-ESN). The flows under investigation are chaotic and 2D turbulent.

Online parameter inference for the simulation of a Bunsen flame using heteroscedatic Bayesian neural network ensembles

M. Croci[1], U. Sengupta[1] and M. Juniper[1]

[1] University of Cambridge, Cambridge CB2 1PZ, UK

The prediction and control of thermoacoustic instability is a persitent challenge in jet and rocket engine design. In gas turbines, the drive toward lower NO_x emissions has led to the use of lean premixed combustion, which is particularly susceptible to thermoacoustic instabilities. Thermoacoustic instaiblity is caused by the heat release rate and the pressure being in phase during combustion. Heat release are fluctuations are cuase by flame surface area fluctuations, which in turn are caused by velocity perturbations and flame dynamics. Any physics-based model must therefore contain the flame's response to velocity perturbations. This response can be calculated using detailed CFD simulations of the flame. However, these CFD simulations are expensive. In this work, we use data to tune the parameters of physics-based reduced-order models in order to reduce the cost while retaining as much accuracy as possible.

We suggest an inexpensive and easy to implement parameter estimation technique that uses a heteroscedatic Bayesian neural network trained usng anchored ensembling. The heteroscedatic aleatoric error of the network models the irreducible uncertainty due to parameter degeneracies in our inverse problem, while the epistemic uncertainty of the Bayesian model captures uncertainties which may arise from an input observation's out-of-distribution nature. We ue this tool to perform real-time parameter inference in a 6 parameter G-equation model of a ducted, premixed flame from observations of acoustically excited flames. We train our networks on a library of 1.7 observations of 8500 simulations of the flame edge, obtained using the model with known parameters. Results on the test dataset of simulated flames show that the network recovers flame parameters, with the correlation coefficient between predicted and true parameters ranging from 0.97 to 0.99, and well-calibrated uncertainty estimates. The trained neural networks are then used to infer model parameters from real videos of a premixed Bunsen flam captured using a high-speed camera in our lab. Re-simulation using inferred parameters shows excellent agreement between the real and simulated flames. Compared to Ensemble Kalman Filter-based tools that have proposed for this problem in the combustion literature, our neural network ensemble achieves better data efficiency and our sub-millisecond inference times represent a savings on computational costs by several orders of magnitude. This allows us to calibrate our reduced order flame model in real-time and predict thermoacoustic instability behaviour of the flame more accurately.

Funding: This project has recieved funding from the UK Enginerring and Physical Sciences Research Council (EPSRC) award EP/N509620/1 and from the European Union's Horizon 2020 research and innovation program under the Marie Sklodowska-Curie grant agreement number 766264.

Towards an active learning-based model for prediction of roughness hydrodynamic properties

J. Yang[1], S. Lee[2], S. Bagheri[2], A. Stroh[1], and P. Forooghi[3]

[1] Institute of Fluid Mechanics, Karlsruhe Institute of Technology, Germany
[2] Dept. of Engineering Mechanics, FLOW Centre, KTH, Stockholm, Sweden
[3] Dept. of Mechanical and Production Engineering, Aarhus University, Denmark

Roughness is encountered in a variety of engineering applications since many industrial processes can cause surface roughness, for instance, ice accretion on airplanes, bio-fouling on ships, etc. The roughness on solid surfaces in flow-related applications can enhance the near wall momentum transfer, thus it increases the skin friction. This can translate to significantly altered equipment performances. The increase of skin friction is represented by a downward shift in the mean velocity profile compared with a smooth surface at identical friction Reynolds number Re_τ . This downward shift in the logarithmic layer is known as the roughness function ΔU^+ . Prediction of the roughness function is central to estimation of drag force and modeling of turbulent flow over a rough surface. However, ΔU^+ is not known a priori for any given rough surface, and for every new roughness topography, ΔU^+ needs to be determined using a laboratory or high fidelity numerical experiment, which are both costly. As an alternative to the resource demanding (numerical) experiments, predictive 'roughness correlations' have been extensively used by researchers and engineers. These correlations predict the roughness function solely based on topographical properties of roughness. In recent years, data-driven methods have been successfully used in a wide range of industrial applica- tions. Due to the complex geometry of roughness and the stochastic nature of turbulent flow, the roughness correlations proposed in previous research show difficulties in extrapolating its performance of predicting roughness function outside the range of observation. We argue that in order to achieve a universal roughness predictive model that covers all types of realistic surfaces, an adequately large roughness database with sys- tematically varied roughness properties should be generated. However an obstacle that can stop researchers from fulfilling this task is the cost of determining ΔU^+ for many surfaces using either laboratory or numerical experiments. In other words, cost of 'labeling' data points in a roughness database can be prohibitively large. Therefore, for development of a data-driven roughness model, it is absolutely desired to select the labeled roughness samples as efficiently as possible.

In the present work, we aim at developing an efficient active learning (AL) framework for constructing the roughness database as well as training a deep neural network (DNN) for prediction of roughness function based on this framework. A large roughness repository is generated through a mathematical random rough- ness generation method where the power spectrum (PS) and the PDF of the roughness height are prescribed. The idea is to identify the most representative roughness samples in the repository, based on the AL frame- work, and label them by a painstaking direct numerical simulation (DNS) process. With the proposed AL framework, the model is initially trained by a initial roughness dataset with 20 randomly selected surfaces and subsequently enhanced by a small amount of roughness samples (≈ 20) additional surfaces guided by AL. It is shown that by adding a few representative roughness samples to the training set, the uncertainty of the model prediction can be reduced. The resulting model is also tested on four realistic surfaces with engineering background. With the first iteration of AL, the accuracy of the model predictions for these exemplary realistic surfaces are also significantly promoted. Overall, the results demonstrate the potential of the present AL framework, which will be the basis for future research towards a universal predictive tool.

Acknowledgement Jiasheng Yang and Pourya Forooghi gratefully acknowledge financial support from Friedrich und Elisabeth Boysen-Foundation (BOY-151). Sangseung Lee and Shervin Bagheri gratefully acknowledge support from the Swedish Energy Agency under Grant number 51554-1 and Swedish Foundation for Strategic Research (FFL15-001).

Unsupervised identification of motifs in turbulent flows using Latent Dirichlet Allocation

M. Frihat[1], N. Malhomme[1], B. Podvin[1], L. Mathelin[1], Y. Fraigneau[1], and F. Yvon[1]

[1] Université Paris-Saclay, CNRS, LIMSI, 91400 Orsay, France

The identification of coherent structures in turbulent flows is a recurrent problem. The volume of data available requires the development of adapted post-treatment strategies which can benefit from machine learning strategies. Proper Orthogonal Decomposition and Dynamic Mode Decomposition have been successfully used to identify modes, but the support of the modes is not necessary local, which makes them different from coherent structures. they are not directly associated with a probabilistic representation. In this work we consider a clustering method which is based on Latent Dirichlet Allocation (LDA), a statistical technique used in natural language processing. The technique is applied to a collection of snapshots representing Reynolds stress events in a turbulent channel flow at a moderate Reynolds number $Re_\tau = 590$. Different plane sections, as well as a volumetric section, are considered. Examples of motifs in a plane section are given in figure 1[1]. Results are consistent with the wall-attached model. It is found that motifs scale linearly with their distance from the wall, and that the distribution of motifs scale as the inverse of that distance, which is in agreement with the wall-attached model theory.

[1]Due to LaTeX formatting issue, the figure could not be included in this book of abstract. We apologize to the authors.

Sparse reconstruction of flow over a stalled aerofoil using experimental data

D. Carter[1], F. De Voogt[1]n and B. Ganapathisubramani

[1] Dept. of Aeronautical and Astronautical engineering, University of Southampton, Southampton, UK

Recent work has demonstrated the use of sparse sensors in combination with the proper orthogonal de- composition (POD) to produce data-driven reconstructions of the full velocity fields in a variety of flows. The extent of application of these methods reaches far beyond observable flows, such as sparse sensing of atmospheric or ocean flows. More complex flows require a larger basis, obtained from POD, to capture a similar level of accuracy in the reconstruction. As such data driven methods become more challenging due to the increasing size of models required.

In this work, we aim to combine the outcomes from POD based analyses with Machine Learning strate- gies to improve the prediction capabilities using sparse sensors in turbulent flow relevant to aerodynamic applications. We utilize a time-resolved Particle Image Velocimetry dataset obtained in a water channel experiment of a NACA 0012 aerofoil at $Re_C = 75000$ at an angle of attack $\alpha = 12^o$. The flow is stalled at this angle with a large turbulent separation bubble in the suction side of the airfoil that sheds vorticity into the wake chaotically. Such a stalled flow over the airfoil requires a large number of basis (or modes) for reconstruction. This allows us to investigate the extent of data-driven techniques for the reconstruction of complex flows. We compare both POD-based sensor selection strategies and random sensor locations that allow us to predict a reduced-state of the flow field. The reduced state is based on a limited number of POD modes (which is related to the number of sensors that can be used). To further improve the accuracy of reconstruction, non-linear Machine Learning methods based on Shallow Neural Networks (SNN) are used to augment the output from the POD-based technique. Alternatively, SNN can be used as a model to transform the sensor velocities into the corresponding reduced state. Preliminary results indicate that a simple 2-layer network can reduce the reconstruction error for both random selected probes and probes optimized for POD. Limitations of using SNN for these types of problems will be discussed.

Reduced order modeling for shear layer control over an inclined step

A. Colon de Carvajal[1,], P. Gilotte[2], and I. Mortazavi[1]

[1] CNAM, LM2N, 75003 Paris, France
[2] Plastic Omnium, Intelligent Exterior Systems, 01150 Sainte-Julie, France

Pressure gradient behind a detachment zone is always difficult to predict. The flow detachment induced by an inclined surface could help understanding mechanisms that are important to cpature. Experiments peformed and described in Stela et al. (*J. Fluid Mech.*, 2017) explain the strong influence of the shear layer characteristics in the flow reattachment process. It could therefore be intestering to contribute to this phenomena description thanks to a reduced order model established with dynamic mode decomposition (DMD). The current study is based on 3D computational results obtained with a LES solver using a Least-Squares Galerkin emthod. The original uncontrolled flow and a successfully controlled flow are compared to analyze into detail the interaction between the shear layer and the flow recirculation. The flow control is performed thanks to periodic jets re-energetizing the shear layer at the limit of a detachment edge. This momentum addition to the shear layer could, at certain frequencies, induce an increase of the pressure on the ramp in the recirculation zone. A DMD analysis of the flow will shed light on the frequencies that are energitcally modified.

The anlyzed shear layer is generated from the detachment produced by an inclined surface at an angle of 25°. Inflow periodic conditions at the shap edge enable to increase the momentum leading to a reduction of the recirculation zone as well as the turbulent kinetic energy. However, the link between these inflow conditions and its effect on the flow behaviour need to be further studied to better understand the shear layer dynamics. Therefore, DMD allows the decomposition into different frequency modes that are involved in this energy transfer. This presentation will detail the different steps which are necessary to perform this decomposition and will contribute to the energy transfer mechanism.

A transfer learning framework to learn the Hama roughness function from a small dataset and empirical correlations

Sangseung Lee[1], J. Yang[2], P. Forooghi[3], A. Stroh[2], and S. Bagheri[1]

[1] Dept. of Engineering Mechanics, FLOW Centre, KTH, Stockholm, Sweden
[2] Institute of Fluid Mechanics, Karlsruhe Institute of Technology, Germany
[3] Dept. of Mechanical and Production Engineering, Aarhus University, Denmark

Nearly all surfaces in fluid-related industries are rough at their operating Reynolds numbers, and this rough- ness generates additional drag compared to ideally smooth surfaces. Moreover, roughness of surfaces can increase after being exposed to flows because of fouling or wear. Therefore, regular examination of surface roughness and its drag is crucial to prevent excessive energy loss and carbon emission. The additional drag induced by roughness can be calculated by measuring the downward shift in the inner-scaled mean stream- wise velocity of flow over a rough surface compared to the flow over a smooth surface. This downward shift is known as the Hama roughness function. The two main constituents that govern the Hama roughness function are the rough surface topography and the friction velocity. Thus, full interactions between flow and rough structures must be captured, or at least accurately modeled, to calculate the Hama roughness function.

For realistic surfaces with irregular rough structures, there are no universal models that can accurately reproduce the effect from interactions between flow and rough structures due to the high-dimensional space of surface features. Accordingly, high-resolution numerical simulations or experiments are needed to accu- rately measure the Hama roughness function. In industries, the high cost for performing simulations and experiments obstructs regular measurements of drag on rough surfaces, making it difficult to plan cycles for cleaning or replacing surfaces. The recent developments in neural networks have shown the potential of estimating drag of rough surfaces without expensive simulations or experiments. Nevertheless, the difficulty of obtaining a large number of data samples to train a network from scratch is still deterring the practical usage of neural networks in fluid-related industries.

In this study, we aim to learn a mapping of surface topography to the Hama roughness function from a small number of data samples (~ 10). We propose a transfer learning framework that augments a network with an ensemble of known empirical correlations of drag on rough surfaces. The developed framework is found to improve the learning of the Hama roughness function compared to existing methods. This framework can be applied to practical applications where only a limited number of data samples is acquirable.

Acknowledgement This work was supported by the Swedish Energy Agency under Grant number 51554-1, Swedish Foundation for Strategic Research (FFL15-001), and Friedrich und Elisabeth Boysen-Foundation (BOY-151).

Cluster-based network modeling of complex dynamical systems

R. Semaan[1], D. Fernex[1], and B. Noack[2, 3]

[1] TU Braunschweig, Institute of Fluid Mechanics, Braunschweig, Germany
[2] Hermann Föttinger Institut, TU Berlin, Germany
[3] Center for turbulence control, Harbin Institute of Technology, Shenzhen, China

Climate, epidemiology, brain activity, financial markets, and turbulence constitute examples of complex systems. They are characterized by a large range of time and spatial scales, intrinsic high dimensionality, and nonlinear dynamics. Dynamic modeling for the long-term features is a key enabler for understanding, state estimation from limited sensor signals, prediction, control, and optimization. Data-driven modeling has made tremendous progress in the past decades, driven by algorithmic advances, accessibility to large data, and hardware speedups. Typically, the modeling is based on a low-dimensional approximation of the state and system identification in that approximation.

In this conference, we present a novel modeling paradigm starting with a time-resolved snapshot set. We liberate ourselves from the requirement of a low-dimensional subspace or manifold for the data and the ana- lytical simplicity assumption of the dynamical system. The snapshots are coarse-grained into a small number of centroids with clustering. The dynamics is described by a network model with continuous transitions be- tween the centroids. The resulting cluster-based network modeling (CNM) uses time-delay embedding to identify models with an arbitrary degree of complexity and nonlinearity. The methodology is developed within the network science and statistical physics frameworks. The talk shall present the latest advances in CNM and demonstrates its capabilities on a range of applications, such as the Lorenz attractor, ECG heartbeat signals, Kolmogorov flow, and a high-dimensional actuated turbulent boundary layer. Even the notoriously difficult modeling benchmark of rare events in the Kolmogorov flow is solved.

Comparison of drag correlation functions for ellipsoidal particles derived theoretically and via genetic programming

T. Kiwitt[1], M. Meinke[1], and W. Schröder[1],

[1] Institute of Aerodynamics and Chair of Fluid Mechanics, RWTH Aachen University, Germany

With the rise in computational power, artificial intelligence (AI) has offered unprecedented possibilities such as, e.g., automatic vehicle driving, disease detection, or the investigation of non-linear physical systems. The possible areas in the latter subject are very broad and can range from the general understanding of non-linear dynamics, over assistance in the evaluation of experimental analysis, to the modulation of drag.

Particle-laden flows are of utmost importance in a wide variety of applications in natural and technical environments. Recently, the effort of using renewable energy sources such as biomass particles has increased. The geometry of biomass particles, which are, e.g., nut shells or wood chips, can no longer be approximated by spheres, instead they are of ellipsoidal shape. For heavy rigid particles, the expressions used to de- scribe the particle behavior in Lagrangian point-particle models are mostly reduced to the drag force. It is therefore vital to derive an accurate correlation function to properly predict the drag between the particle and the fluid to conduct highly accurate numerical simulations and maximize the process efficiency and safety.

In this contribution, a comparison between correlation functions for the drag C_{drag} of an ellipsoidal particle in uniform flow conditions derived theoretically and by an artificial intelligence approach, the lat- ter being represented by a genetic programming (GP) method, is conducted. The accuracy, complexity, and applicability of each approach will be discussed and individual advantages and limitations will be argued.

The results indicate that the theoretically derived equation shows superior accuracy in exchange for higher complexity, i.e., the human-derived equation shows a mean deviation of $\overline{\Delta C_{drag}} = 0.83\%$ while the equation generated by the GP approach yields an accuracy $\overline{\Delta C_{drag}} = 1.65\%$. Comparing the complexity of both equations, the AI derived equation is shorter and more compact.

Advantages and limitations of both approaches are discussed. The theoretical derivation of a correlation equation is based on physical knowledge. In contrast, AI-derived correlation equations allow an automated approach which can be easily extended to large data sets.

In an additional investigation the GP algorithm is trained to predict whether or not flow separation on the surface of an ellipsoid will occur based on the input parameters Reynolds number Re, particle aspect ratio β, and particle inclination angle ϕ. The comparison with fully resolved simulation data show that the algorithm is able to predict the onset of flow separation with 94% accuracy.

Poisson CNN: a general purpose neural 2D Poisson solver with applications to CFD

A. Girayhan Ozbay[1], A. Hamzehloo[1], S. Laizet[1], P. Tzirakis[2], G. Rizos[2], and B. Schuller[2]

[1] Dept. of Aeronautics, Imperical College London, UK
[2] Dept. of Computing, Imperial College London, UK

The Poisson equation plays a central role in the computation of the pressure corrections when solving the incompressible Navier-Stokes equations in computational fluid dynamics (CFD). Machine learning methods offer a unique capability to accelerate this step. We introduce Poisson CNN, a novel convolutional neural network (CNN) architecture to estimate the solution of the Poisson equation on 2D Cartesian grids, capable of making predictions for problems with differing grid resolutions/sizes and arbitrary Dirichlet or Neumann boundary conditions without re-training. The boundary condition flexibility is achieved by an innovative approach whereby the problem is decomposed into one homogeneous Poisson problem plus four inhomoge- neous Laplace sub-problems, with one sub-model per sub-problem type; Homogeneous Poisson NN (HPNN) and Boundary Condition NN (BCNN), respectively. Training is conducted on a synthetic dataset with 192 to 384 gridpoints per dimension, using a novel loss function approximating the continuous Lp norm between the prediction and the target.

The proposed Poisson CNN achieves high accuracy in a variety of practical tasks, despite training on synthetic data. On a purely synthetic validation set, the Poisson CNN achieves mean absolute percentage errors (MAPE) of just 8.5%. The individual sub-models were compared to models commonly utilized in machine learning literature; using the same number of parameters, the HPNN achieved MAPE values 74% lower than a U-Net on the same task while the BCNN netted a 64% reduction compared to a Bi-LSTM. In a CFD context, within a Taylor-Green Vortex (TGV) simulation at $Re = 1.0$ utilizing single-cycle Multigrid as the Poisson solver, using initial predictions from the Poisson CNN enabled a 99.3% reduction in the ℓ_2 pressure error at time $t = 1.0$ versus zero initial predictions. Furthermore, it was found that the Poisson CNN can accelerate Multigrid convergence on grid sizes far larger than those encountered in training, reaching up to 4500×4500. In terms of wall-clock runtime, on an Nvidia V100, the Poisson CNN is similar to Multigrid on 384×384 grids but is 5 times faster on 4500×4500 grids.

Kernel Learning for Robust Dynamic Mode Decomposition

P. J. Baddoo[1], B. Herrmann[2, 3], B. J. McKeon[4], and S. L. Brunton[2]

[1] Dept. of Mathematics, Massachusetts Institute of Technology, Cambridge, MA 02138, USA
[2] Dept. of Mechanical Engineering, University of Washington, Seattle, WA 98195, USA
[3] Institute of Fluid Mechanics, TU Braunschweig, 38108 Braunschweig, Germany
[4] Gradute Aerospace Lab., California Institute of Technology, Pasadena, CA 91125, USA

Discovering interpretable patterns and models from high-dimensional data is one of the principal challenges of scientific machine learning, with the potential to transform our ability to predict and control turbulent systems. Generalized linear regression techniques, such as the dynamic mode decomposition (DMD), and the sparse identification of nonlinear dynamics (SINDy), are widely used because they are computationally efficient, require less data than neural networks, are highly extensible, and provide interpretable models. However, these approaches are either challenged by nonlinearity (e.g., DMD) or don't scale to high-dimensional systems (e.g., SINDy). In this work, we develop a custom kernel regression algorithm to learn accurate, efficient, and interpretable data-driven models for strongly nonlinear, high-dimensional systems. This approach scales to very high-dimensional systems, unlike SINDy, yet still accurately disambiguates the linear part of the model from the implictly defined nonlinear dynamics. Thus, it is possible to obtain linear DMD models, local to a given base state, that are robust to strongly nonlinear dynamics. Essential to the framework is the construction of a 'dictionary' of samples that appreciably contribute to the dynamics. Restricting the regression to this carefully chosen dictionary reduces overfitting, improves the condition number of the problem, and renders the problem computationally tractable. We also demonstrate that there is significant flexibility to incorporate known physical laws (e.g., types of nonlinearities, symmetries, multi-physics) into kernel design. We apply our algorithm to a range of dynamical systems and partial differential equations commonly used to model turbulent flows. The method efficiently and accurately extracts the underlying linear operators of the nonlinear Lorenz system, the viscous Burgers' equations and the chaotic Kuramoto-Sivashinsky equation using only data measurements. The disambiguation of the linear operator from the nonlinear forcing opens the door to purely data-driven resolvent analysis of nonlinear problems in future works. The framework can be formulated in a compltely online fashion, thus enabling real-time prediction and control of turbulent systems.

A manifold learner for wake flows: an application to the fluidic pinball

E. Farzamnik[1], A. Ianiro[2] S. Discetti[2], N. Deng[3] B. Noack[4, 5] and V. Guerrero[1]

[1] Dept. of statistics, Universidad Carlos III de Madrid, Spain
[2] Aerospace Engineering Research Group, Universidad Carlos III de Madrid, Spain
[3] Institute of Mechanical Sciences and Industrial Applications, ENSTA-Paris, France
[4] Center for turbulence control, Harbin Institute of Technology, Shenzen, China
[5] Hermann-Föttinger Institut, TU Berlin, Germany

Reduced-order models (ROM) are highly used to analyze, model, estimate, and control the flows. Some of the traditional methods which perform linear mapping did not show satisfactory performance in the transient regimes of highly turbulent flows. However, current nonlinear methods such as Isometric mapping or Isomap, which uses the geodesic distances to preserve the dataset's intrinsic geometry in the high- dimensional space, provide promising results. In this work, we propose a manifold learner encoder and a K-Nearest Neighbors (K-NN) decoder to study the complex evolution of the fluidic pinball configuration. We show that the developed encoder-decoder tool in this work can unravel some hidden flow phenomena, provide an interpretable relation to some flow features like force coefficients and distinguish the flow regimes by finding the manifolds in low dimensional space while providing outstanding robustness compared to other similar tools. Moreover, the developed decoder in this work shows an outstanding advantage in terms of reconstruction error compared to traditionally used POD. The promising outcomes from using these techniques to study complex flow dynamics provide an expansive playground for further study on developing efficient flow control systems.

Acknowledgement: This work was supported by the research project PITUFLOW-CM-UC3M, funded by the call "Programa de apoyo a la realizacioon de proyectos interdisciplinares de I+D para joovenes investigadores de la Universi- dad Carlos III de Madrid 2019-2020" under the frame of the Convenio Plurianual Comunidad de Madrid-Universidad Carlos III de Madrid.

Thursday 17th

Nonlinear model reduction from equations and data to spectral submanifolds

G. Haller[1], S. Jain[1], and M. Cenedese[1]

[1] Institute for Mechanical Systems, ETH Zurich, Switzerland

Determining the forced response of very large, nonlinear mechanical systems remains a major challenge despite advances in computational power. Projection-based model reduction techniques have been in use for this purpose but they to rely on ad hoc mode selection and produce a priori unknown errors. In this talk, we discuss a recent mathematical alternative to these approaches based on spectral submanifolds (SSMs) [1], which are very low dimensional, attracting invariant surfaces in nonlinear systems. Reduction to SSMs turns out to yield previously unimaginable speed-ups in solving large finite-element models [2]. Very recent results also show that SSMs and their reduced dynamics can be constructed directly from data [3]. We will illustrate these results on high-dimensional mechanical systems and experimental data sets. We will also show that these reduced-order models are powerful to make accurate predictions for detailed nonlinear behavior that numerical continuation codes would normally miss.

In a broader context, even the development of the governing equations for complex dynamical phenomena in solid and fluid mechanics are often out of reach. Examples include beam oscillations with unknown material nonlinearities or fluid-structure interactions with complex geometries. However, as long as these systems can, in principle, be modelled by PDEs with an invertible linearized flow, the theory of SSMs remains valid for them. This creates an exciting perspective to learn low-dimensional nonlinear reduced-order models directly from experimentally measured data for these systems. We sketch the underlying theoretical considerations and show initial successes of this approach on beam oscillations and separated shear flow data.

Koopman eigenfunctions estimation from reproducing kernel Hilbert space manifold and ensemble forecast

B. Hug[1], E. Mémin[1], and G. Tissot[1]

[1] INRIA ennes Bretagne Atlantique, IRMAR-UMR CNRS, Rennes, France

This study aims at proposing a new framework to perform ensemble-based estimations of dynamical trajectories of a geophysical fluid flow system. To perform efficient estimations, the ensemble members are embedded in a set of evolving reproducing kernel Hilbert spaces (RKHS) defining a (Hilbert) manifold of spaces. The method proposed here is designed to deal with very large scale systems such as oceanic or meteorological flows, where it is out of the question to explore the whole attractor, neither to run very long time simulations. Instead, we propose to learn the system locally, in phase space, from an ensemble of trajectories. The novelty of the present work relies on the fact that the feature maps between the native space and the RKHS manifold are transported by the dynamical system. This creates, at any time, an isometry between the tangent RKHS at time t and the initial conditions. This has several important consequences. First, the kernel evaluations are constant along trajectories, instead to be attached to a system state. By doing so, a new ensemble member embedded in the RKHS manifold at the initial time can be very simply estimated at a further time. This framework displays striking properties. The Koopman and Perron–Frobenius operators on such RKHS manifold are unitary, even though the system might be non invertible. They are furthermore uniformly continuous (with bounded generators) and diagonalizable. As such they can be rigourously expended in exponential forms. This set of analytical properties enables us to provide a practical estimation of the Koopman eigenfunc- tions. In the proposed strategy, evaluations of these Koopman eigenfunctions at the ensemble members are exact. To perform robust estimations, the finite-time Lyapunov exponents associated with each Koopman eigenfunction (which are easily accessible on the RKHS manifold as well) are determined. On this basis, we are able to filter the kernel by removing contributions of the Koopman modes that exceed the predictability time. We show that it leads to robust estimations of new unknown trajectories. The methodology is demonstrated on a barotropic quasi-geostrophic model of a double gyres. After comparing various kernels and provided guidelines to adapt the kernel with the spread of the ensemble, we show isometry and Koopman-filtered reconstructions.

Data-driven flow modeling using machine learning and data assimilation

N. Kumar[1], F. Kerhervé[1], and L. Cordier[1],

[1] Institut Pprime, CNRS, Université de Poitiers, ISAE-ENSAM, Poitiers, France

In flow control, Reduced-Order Models based on Proper Orthogonal Decomposition (POD ROMs) are often employed as a surrogate model of high-fidelity models. In practical applications, three difficulties are encountered: 1) it is necessary to know the governing equations of the dynamics to derive the reduced-order model by Galerkin projection of the model onto the POD modes, 2) the POD ROMs represent only one dynamical configuration and 3) the long-term stability of the POD-ROM is often difficult to ensure. In this paper, we deal successively with these three aspects. A regression model based on artificial neural network is proposed as a surrogate alternative to the POD ROM. This method addresses the limitations of POD ROM – the lack of an a priori guarantee of stability, and requirement of closure formulation to account for the unresolved modes. The model maps the reduced coefficients of the high-fidelity solution in low-dimensional space to a given set of parameter values. This non-intrusive modelling suits the problems with no or limited knowledge of the physical system. Here, a novel multistep, residual-based, parametrized neural network framework is proposed and is augmented with data assimilation (DA) to provide accurate long-term dynamical predictions. The proposed non-intrusive approach is used to recover the dynamical states in numerical and experimental fluid flow problems. The neural network based identification has been found to provide sufficiently accurate initial estimates. Deviations in the long-term prediction are mitigated by augmenting the framework with DA. This approach also allows the estimation of dynamics corresponding to parameters not considered in the model training set.

Galerkin force model for transient and post-transient dynamics exemplified for the fluidic pinball

N. Deng[1, 2], B. Noack[3] M. Morzynski[4], and L. Pastur[1]

[1] IMSIA, ENSTA-Paris, Institut Polytechnique de Paris, 91120 Palaiseau, France
[2] Université Paris-Saclay, CNRS, LIMSI, 91400 Orsay, France
[3] Center for turbulence control, Harbin Institute of Technology, Shenzen, China
[4] Chair of Virtual Engineering, Poznan University of Technology, 60-965 Poznan, Poland

The literature on aerodynamic forces on bodies associated with the proper orthogonal decomposition (POD) or any other Galerkin model is suprisingly sparse. On the one hand, force computations are at the heard of engineering fluid mechanics. On the other hand, systematic investigations and interpretations of the aerodynamic force in the Galerkin framework are mostly missing. As the forces depend on the viscous and pressure fields, it is challenging to model the force with the velocity-based POD modes. The pioneering early work of Shiels & Jeon reveals that the instantaneous forces on the body can be expressed with only the velocity fields and their derivatives. Liang & Dong applied it to the velocity-based POD modes, and derived a force expression in terms of the force of each POD mode and the force from the interaction between the POD modes. The Galerkin force model proposed in this work reveals that any force component is a constant-linear-quadratic function of the mode amplitudes. It provides a significant opportunity to achieve nonlinear modelling of the force dynamics and advances our understanding of the elementary degrees of freedom that contribute to the force.

The aim of this work is to present an aerodynamic force model in the Galerkin framework. For the Galerkin approximation of a bluff-body flow, the instantaneous force on the body is derived as a constant- linear-quadratic function of the mode amplitudes from first principles. The drag and lift force formulae can be further simplified for the mean-field model using symmetry properties and sparse calibration, thereby indicting the drag- and lift-producing modes. In the presentation, the Galerkin force model is exemplified for the unforced fluidic pinball, a two- dimensional flow around three fixed cylinders with one radius distance to each other in an equilateral triangle arrangement. Based on the least-order mean-field model, the resulting force model can successfully reproduce the unsteady force evolution for the transient and post-transient dynamics with six different Navier-Stokes solutions. We foresee many applications of the Galerkin force model for other bluff bodies and flow control.

Complementary deep reduced order model

E. Menier[1, 2], M. A. Bucci[1], M. Yagoubi[1], and M. Schoenauer[2]

[1] IRT - System X, Palaiseau, France
[3] LISN, INRIA, CNRS, Université de Paris-Saclay, Orsay, France

Reducing simulation time is critical for applications such as closed loop control or iterative design op- timisation. In this context, model reduction techniques have become a growing area of research in the last decades. While research efforts have mainly been centered around feature based approaches like POD, BPOD or DMD, direct approaches leveraging Deep Neural Networks have been proposed in recent years with great success. Despite these promising results, neural network architectures provide little to no physical guarantees, and have limited interpretability. On the other hand, feature based methods often reconstruct the final solution through a linear combination of modes embedded with physical constraints. However, this often comes at the cost of loss of information and increased error rates.

POD-Galerkin models are a perfect example of this trade-off between physical guarantees and performance loss. These models have been shown to be very efficient for the reduction of linear systems, but they are extremely limited when applied to nonlinear systems such as the Navier-Stokes equations. For example, Noack et al. have shown that a simple 3 equations model was able to capture the oscillatory dynamics of a flow over a cylinder, but failed to correctly predict the transition time and trajectory from a steady point of the system to its oscillatory regime.

To address these shortcomings, we propose to add a closure term to POD-Galerkin models to correct their dynamics. Observing that the information lost during the projection on the POD basis can be retrieved by considering the past states of the system, we use simple neural networks in combination with delay differential equations to reconstruct the required correction. We show that a satisfactory model can be trained through the Neural ODE framework to learn a memory based correction from simulation data. The final architecture can be compared to a time-continuous recurrent neural network.

With this approach, we preserve the simple structure and low computational cost of Galerkin models while improving their performance. Using the 3 modes model example from [4], we show that the corrected ROM reproduces perfectly the original transition trajectory, and generalises well to unseen initial conditions. On-going work is concerned with validating and improving the proposed approach by applying it on the more challenging chaotic pinball case.

Learning how structures form in drif-wave turbulence

R. Heinonen[1, 2], and P. Diamond[1],

[1] Dept. of Physics, University of California, San Diego, USA
[2] Dept. of Physics, University of Rome, Tor Vergata, Italy.

In magnetically confined plasma, instabilities associated with radial pressure gradients give rise to drift- wave turbulence (DWT). Anomalous transport, structure formation, and virtually all other aspects of DWT dynamics are encoded in turbulent fluxes which are generated by cross-correlations between fluctuating quantities. Computing these cross-correlations may be considered the central problem of plasma turbulence modeling and is crucial to understand confinement properties. However, doing so analytically is a notorious challenge that always requires the use of successive (and sometimes questionable) approximations, such as the introduction of a small parameter, a closure for higher-order moments, or the imposition of an ad-hoc mathematical model.

In this work, we instead use supervised learning to infer models for key turbulent fluxes from simulation. We use numerical solutions of the 2-D Hasegawa-Wakatani system, a simple but self-consistent model for collisional DWT, to train a neural network which outputs the local turbulent particle flux and Reynolds stress as functions of local mean gradients, flow properties, and turbulence intensity. The neural network detects a previously unreported, non-diffusive particle flux which is proportional to the gradient of vorticity. We recover this flux with a simple analytic calculation, and identify it as a simple but novel route to staircase-like pattern formation. Using this supervised learning approach, we also uncover a Cahn-Hilliard-type model for the generation of zonal flow via Reynolds stress, which agrees with but finds corrections to previous theoretical work. Together with the particle flux, we thus obtain a simplified (but still self-consistent) 1-D model for the turbulent dynamics directly from simulation data. We solve this model numerically and compare to the numerical solutions of the full 2-D system. We discuss the importance of symmetry to our supervised learning method, the method's portability to other applications, and its range of validity.

Funding: This work received funding from the United States Department of Energy under Award Number DE-FG02-04ER54738 and from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement No. 882340).

Identification of sea level pressure anomaly patterns using Latent Dirichlet Allocation

L. Fery[1, 2], B. Dubrulle[3] B. Podvin[4] F. Pons[1] and D. Faranda[1, 5, 6]

[1] Laboratoire des Sciences du Climat et de l'Environnement, CEA Saclay l'Orme des Merisiers, UMR 8212 CEA-CNRS-UVSQ, Université Paris-Saclay & IPSL, 91191, Gif-sur-Yvette, France
[2] Department of Physics, Ecole Normale Supérieure de Lyon, 69364, Lyon, France
[3] SPEC, CEA, CNRS, Université Paris-Scalay, F-91191 CEA Saclay, Gif-sur-Yvette, France
[4] LISN, CNRS, Université Paris-Scalay, 91405 Orsay, France
[5] London Mathematical Laboratory, 8 Margravine Gardens, London, W6 8RH, UK
[6] LMD/IPSL, Ecole Normale Superieure, PSL research University, 75005, Paris, France

Atmospheric circulation in middle latitudes is often represented with weather regimes, which are typical field configurations of relevant observables - such as geopotential height or sea level pressure - determined by pattern recognition methods. Each weather regime can be considered as a mixture of basic synoptic objects, which are cyclones and anticyclones. This combination makes it difficult to disentangle shifts in these structures recurrence and intensity, and in particular those relevant to extreme events. Here we propose a change of perspective by applying Latent Dirichlet Allocation (LDA), a generative statistical model for collections of discrete data which is typically used as a topic model for text documents, to a set of snapshots featuring daily sea level pressure anomaly. LDA acts as a soft clustering technique providing a representation of a daily map in terms of a combination of motifs, which are latent patterns inferred from the dataset. We notice that the motifs correspond to cyclones and anticyclones, the basic structures of weather regimes. Furthermore, we show that the weights provided by LDA are a practical way to characterize the effects of climate change on the recurrence and intensity of these structures and to identify precursors of extreme events.

Learning subgrid-scale turbulence models: coupling back-propagation with the adjoint flow equations

J. MacArt[1], J. Sirignano[2] and J. Freund[3]

[1] Department of Aerospace and Mechanical Engineering, University of Notre Dame, IN, USA
[2] University of Oxford, UK
[3] Department of Aerospace Engineering, University of Illinois at Urbana–Champaign, IL, USA

The weights of a deep neural network model are optimized in conjunction with the governing flow equations to provide a model for sub-grid-scale stresses in a temporally developing plane turbulent jet at Reynolds number $Re_0 = 6000$. The objective function for training is first based on the instantaneous filtered velocity fields from a corresponding direct numerical simulation, and the training is by a stochastic gradient descent method, which uses the adjoint Navier–Stokes equations to provide the end-to-end sensitivities of the model weights to the velocity fields. In-sample and out-of-sample testing on multiple dual-jet configurations show that its required mesh density in each coordinate direction for prediction of mean flow, Reynolds stresses, and spectra is half that needed by the dynamic Smagorinsky model for comparable accuracy. The same neural-network model trained directly to match sub-grid-scale stresses—without the constraint of being embedded within the flow equations during the training—fails to provide a qualitatively correct prediction. The coupled formulation is generalized to train based only on mean-flow and Reynolds stresses, which are more readily available in experiments. This provides a robust model, which is important, though a somewhat less accurate prediction for the same coarse meshes, as might be anticipated due to the reduced information available for training. The anticipated advantage of the formulation is that the inclusion of resolved physics in training increases its capacity to extrapolate. This is assessed for the case of passive scalar transport, for which it outperforms established models due to improved mixing predictions. Figure 1[2] shows a demonstration of the advantage of the em- wise velocity with an ML model trained as an bedded training for a planar turbulent jet using a coarse mesh. Although a priori training, which minimizes the sub-grid-scale stress mismatch, is able to reproduce the stress nearly perfectly (figure 1 a), the results are poor when the model is included in the governing equations and they are evolved in time (figure 1 b), for the model's interactions with the governing equations are not sufficiently constrained. In contrast, the embedded training, performed with the neural-network back-propagation algorithm coupled with the corresponding adjoint-based sensitivity of the governing equations, provides a model that drives the solution of the governing equations toward the target data, which here are instantaneous filtered velocity fields. Solving with the embedded model tracks the corresponding direct numerical simulation closely, even on the relatively coarse mesh. It also provides effective augmentation—modestly less accurate but similarly robust—for similar out-of-sample free shear flows (not shown).

[2]Not shown in this book of abstract because of LaTeX issues. We apologize to the authors.

This material is based in part upon work supported by the Department of Energy, National Nuclear Security Administration, under Award Numbers DE-NA0002374 and DE-NA0003963. This research is part of the Blue Waters sustained-petascale computing project, which is supported by the National Science Foundation (awards OCI-0725070 and ACI-1238993) and the State of Illinois. Blue Waters is a joint effort of the University of Illinois at Urbana–Champaign and its National Center for Supercomputing Applications.

Multi-agent reinforcement learning of wall-modeled large-eddy-simulation

H. J. Bae[1, 2], P. Koumoutsakos[1, 3]

[1] Institute of Applied Computational Science, Havard University, Cambridge, MA 02138, USA
[2] Gradute Aerospace Lab., California Institute of Technology, Pasadena, CA 91125, USA
[3] Computational Science and Engineering Lab., ETH Zurich, CH-8092, Switzerland

Simulations of wall-bounded turbulent flows have become a key element in the design cycle of wind farms and aircraft, and a major factor in the predictive capabilities of simulations of atmospheric flows. Due to the high Reynolds numbers associated with these flows, direct numerical simulations (DNS), where all scales of motion are resolved, are not attainable with current computing capabilities. Large-eddy simulations (LES) aim to reduce the necessary grid requirements by resolving only the energy-containing eddies and modeling the smaller scale motions. However, this requirement is still hard to meet in the near-wall region, as the stress-producing eddies become progressively small, scaling linearly in size with the distance to the wall. In turn, modeling the near-wall flow such that only the large-scale motions in the outer region of the boundary layer are resolved, wall-modeled LES (WMLES) stands as the most feasible approach compared to wall-resolved LES or DNS. The use WMLES for engineering applications is expected to narrow the number of wind tunnel experiments, reducing both the turnover time and cost the design cycle.

We propose multi-agent reinforcement learning (MARL) for the development of wall models for LES. Reinforcement learning identifies optimal strategies for agents that perform actions, contingent on their information about the environment, and measures their performances via scalar reward functions. In this work, discretization points act also as cooperating agents that learn to supply the LES closure model, and their actions compensate for both the closure terms and errors associated with the numerics of the flow solver.

In the case of WMLES, the performance of the MARL can be measured by comparing the statistical properties of the simulation to those of reference data such as the wall-shear stress. MARL does not rely on a priori knowledge but rather aims to discover active closure policies according to patterns in the flow physics captured by the filtered equations. The respective wall models are robust with respect to the numerical discretizations, as these erros are taken into consideration in the training process. Furthermore, the model discovery method can be readily extended to complex geometries and different flow configurations, such as flow over rough surfaces and stratified and compressible boundary layers. We demonstrate the potential of this approach on WMLES of turblent high-Reynolds number channel flow and turbulent boundary layer. The MARL-based wall model is able to reproduce flow quantities obtained by fully-resolved simulations and performs as well as the widely-used Reynolds-averaged Navier-Stokes models that have been tuned for this particular flow configuration.

Acknowledgements The authors acknowledge the support of Air Force of Scientific Research (AFOSR) Multidisciplinary University Research Initiative (MURI) project : Prediction, Statistical Quantification and Mitigation of Extreme Evens Caused by Exogeneous Causes or Intrinsic Instabilities under grant number FA9550-21-1-0058.

Turbulence modeling using CFD-driven symbolic identification

D. Bezgin[1], and N. Adams[1]

[1] Department of Mechanical Engineering, Chair of Aerodynamics and Fluid Mechanics, TU Munich, Germany

Complex dynamic interactions across multiple scales render the numerical simulation of turbulence a difficult problem. Reynolds-averaged Navier-Stokes (RANS) equations are widely used in practice and are traditionally closed by employing the eddy viscosity hypothesis and the assumption of isotropy. A different appraoch is taken by so called probability density function (PDF) turbulence models which solve a transport equation for the on-point, one-time PDF of turbulent fluctuating quantities. Instead of discretizing the Fokker-Planck equation directly, classical PDF methods make use of Monte-Carlo methods in which an ensemble of particles is advected by a corresponding stochastic differential equations. Recently, machine learning models, especially neural network based-approaches, have been applied to turbulence modeling. We propose to use latent neural ordinary differential equations (NODE) as parametrizable generative models for learning the PDF transport of fluctuating flow quantities such as velocity fluctuations. A latent NODE model learns a mapping between observation and latent space and the coresponding latent space dynamics. Thereby, the continuous latent space dynamics are determined by a neural network. Given time series data of turbulent velocity fluctuations, the generative model is able to learn the latent space dynamics of the PDF of these fluctuations. After proper training, we can sample an ensemble of initial conditions from the learned latent distribution and propagate them forward in time by the NODE. The resulting latent trajectories are then decoded to velocity space yielding realizations of the instantaneous flow field. By successive ensemble-averaging, we obtain the Reynolds stresses and close the RANS equations. We show proof of concept by learning PDFs for the return to isotropy of homogeneous shear turbulence. DNS simulations of homogeneous shear-released turbulence are obtained by a spectral solver. Early results indicate that NODE are in fact able to learn the PDF transport equations and provide a powerful tool for data-driven PDF turbulence models.

Reconstruction of turbulent data with deep generative models for semantic inpainting from TURB-Rot database

M. Buzzicotti[1], T. Li[2], F. Bonaccorso[1, 3], P. Clark Di Leoni[4], and L. Biferale[1]

[1] Dept. of Physics & INFN, University of Rome Tor Vergata, 00133 Rome, Italy
[2] Dept. of Mechanics and Aerospace Engineering, Southern University of Science and Technology, China
[3] Center for Life Nano Science, Istituto Italiano di Tecnologia, 00161 Rome, Italy
[4] Dept. of Mechanical Engineering, Johns Hopkins University, Baltimore, 21218 Maryland, USA

We study the applicability of tools developed by the computer vision community for *feature learning* and *semantic image inpainting* to perform data reconstruction of fluid turbulence configurations. The aim is twofold. First, we explore on a quantitative basis the capability of convolutional neural networks embedded in a deep generative adversarial model to generate missing data in turbulence, a paradigmatic high-dimensional chaotic system. In particular, we investigate their use in reconstructing two-dimensional damaged snapshots extracted from a large database of numerical configurations of 3D turbulence in the presence of rotation, a case with multi-scale random features where both large-scaled organised structures and small-scale highly intermittent and non-Gaussian fluctuations are present. Second, following a reverse engineering approach, we aim to rank the input flow properties (features) in terms of their qualitative and quantitative importance to obtain a better set of reconstructed flow fields. We present two approaches based on Context Encoders. The first one infers the missing data via a minization of the ℓ_2 pixelwise reconstruction loss plus a small adversarial penalisation. The second searches for the closest encoding of the corrupted flow configuration from a previously trained generator. Finally, we present a comparison with different data assimilation tools, either based on Nudging (an *equation informed* unbiased protocol) well known in the numerical weather prediction community or on Gappy POD developed in the context of image reconstruction. The TURB-Rot database `http://smart-turb.roma2.infn.it`, of roughly 300k 2D turbulent images is released an details on how to download it are given.

Friday 18th

Experimental closed-loop control of an airfoil using linear genetic programming at high Reynolds numbers

P.-Y. Passaggia[1], N. Mazellier[1], and A. Kourta[1]

[1] Université d'Orléans, INSA-CVL, PRISME, 45072 Orléans, France

Flow separation over wings at high angles of attack represents a threat to both the aerodynamic performances and the aeroelastic loads associated with the structure of the aircraft. Flow control aims at mitigating the detrimental effects of massively separated regions using either continuous or pulsed blowing, for instance. Feedback control of such configurations is becoming of increasing interest for the aerospace in- dustry where feedback control can improve both the performance of the control and the amount of energy injected to control separation. Nevertheless, real-time feed- back control at large Reynolds numbers combines major scientific challenges. Both actuators and sensors are required to operate over large ranges of amplitudes and frequencies. In addition, real-time control has to be able to operate these control laws at several kHz in order to tackle the physics of flow separation and insure the feed- back between sensors and actuators. A such feedback loop is intractable unless model reduction is considered or machine learning control-based methods are employed.

Here we implement real-time feedback control using a Linear Genetic Program- ming Control (LGPC) algorithm, based on symbolic programming, to determine ef- fective control laws that improve both the aerodynamic performances and decrease the amount of air injected for the control. These symbolic control laws couple a set of pressure sensors to blowing jets with variable flow rates and are able to identify the key mechanisms leading to stall control. Experimental results obtained for an ON- ERA D airfoil are analysed for two different cost functions where the cost associated with the control effort is varied. In addition, the best control laws are calculated for several angles of attack and for Reynolds numbers ranging between 5×10^5 and 10^6.

Closed-loop control of a separated flow using Reinforcement learning

T. Guégan[1], O. Semeraro[2], M. A. Bucci[3], L. Cordier[1], and L. Mathelin[2]

[1] Institut Pprime, CNRS, Université de Poitiers, ISAE-ENSAM, Poitiers, France
[2] LISN, CNRS, Université de Paris-Saclay, Orsay, France
[3] LISN, INRIA, Université de Paris-Saclay, Orsay, France

In recent years, continuous progress has been made on the performance of air transport systems such as aircraft or helicopters, particularly in terms of flight envelope, radiated noise, maneuverability, vibration level, etc. However, further improvements can be achieved using closed-loop flow control. This technique consists in using measurements from sensors placed on the system to drive some actuators in order to modify the flow in a given way. The interest of closed-loop control schemes is to improve the robustness of the control law against unmodelled disturbances. In usual model-based control approaches, a dynamical model is used to describe the behaviour of the system. This model allows to predict the effect of a given control action and can therefore be used to derive a control strategy for optimal performance. However, a physical model is not always available. In addition to systems whose governing equations are simply unknown or poorly known, there are many situations where solving the governing equations is too slow with respect to the dynamics at play to be useful. While reduced- order models may help in solving an approximate system meeting real-time requirements, they usually lack robustness and can critically lose accuracy when control is applied, resulting in poor performance at best. A different line of control strategy relies on a data-driven approach. In this view, no model is assumed to be known and the control command is derived based on measurements only. Typical of this viewpoint are extremum-seeking, control strategies that rely on system identification techniques that lead to auto- regressive models, subspace methods or realization-type identification algorithms like ERA. Recently, efforts have focused on a genetic programming approach for optimizing the control policy and on the use of a reinforcement learning paradigm. In the present work, we follow up on our earlier effort and consider a reinforcement learning strategy for the closed-loop nonlinear control of separated flows. Specifically, neural networks are used to approximate both the control objective and the control policy, hence the name Reinforcement Learning (RL). We consider the flow over the fluidic pinball in the realistic setting where one can rely only on a few pressure sensors in the wake to learn the system behavior and an efficient control law. The performance of the control strategy will be demonstrated on the reduction of the drag.

Fundings: This work was supported by the French Agence Nationale de la Recherche ANR-17-CE22-0008.

Explorative gradient method for multi-actuator flow control

Y. Li[1], Z. Yang[2], M. Morzynski[3], Z. Qiao[4], S. Krajnovic[4], and B. Noack[1]

[1] Center for turbulence control, Harbin Institute of Technology, Shenzhen, China
[2] Shanghai Automotive WInd TUnnel Center, Tongji University, Shanghai, China
[3] Chair of Virtual Engineering, Poznan University of Technology, Poznan, Poland
[4] Dept. of Mechanics and Maritime Sciences, Chalmers University of Technology, Gothenburg, Sweden

We address a challenge of active flow control—the optimization of many actuation parameters with a limited testing budget. The proposed explorative gradient method (EGM) combines fast gradient-based descent to hitherto known minima with effective exploration of potentially better minima. EGM enforces strict testing budgets and quotas for exploitation and exploration. EGM is applied to net drag power reduction of fluidic pinball by cylinder rotation based on DNS simulation (3 inputs), drag reduction of a 35-degree Ahmed body with steady blowing based on RANS simulation (10 inputs), and a yawed bluff body with zero-net mass-flux jet in experiment (10 inputs). EGM is a versatile optimizer framework with numerous future applications. It cannot only be applied to parameter optimization but also to model-free control law optimization, hitherto performed by genetic programming and deep reinforcement learning.

Gradient-based machine learning control exemplified for the stabilization of the fluidic pinball and the open cavity experiment

G. Cornejo Maceda[1], Y. Li[1] F. Lusseyran[2] M. Morzynski[3] B. Noack[2]

[1] Université Paris-Saclay, CNRS, 91400 Orsay, France
[2] Center for turbulence control, Harbin Institute of Technology, 518058 Shenzhen, China
[3] Dept. of virtual engineering, Poznan University of Technology, PL 60è695 Pozna, Poland

Flow control is at the heart of many engineering applications. In general, control design is challenged by the high-dimensionality of the dynamics, the nonlinearity with many frequencies crosstalk mechanisms and the large time-delay between actuation and sensing. Hence, most closed-loop control studies of turbulence resort to a model-free approach. A key step is the formulation of the control problem as a challenging non-convex optimization problem in which the possibility of sevaral lcoal minima must be expected. Genetic programming control (GPC) has been pioneered by Dracopoulo (1997) over 20 years ago and has been proven to be particularly successful for nonlinear feedback turbulence control in experiments. GPC has consistently outperformed existing optimized control approaches, often with unexpected frequency crosstalk mechanisms. However, the lack of exploitation of local gradients leads to poor convergence to the minimum. This challenge is well known and will be addressed in this study.

In this talk, we employ gradient-augmented machine learning control methods for fast optimization of control laws: the explorative gradient method, combining latin hypercube ssampling and downhill simplex for parametric optimization, and the gradient-enriched machine learning control combining GPC and downhill simplex for feedback control law optimization. The two algorithms comprise exploration and exploitation steps to locate new minima in the search space and populate their neighborhood. We exemplify the algoirhtms with the stabilization of a cluster of three equally distant cylinders – the fluidic pinball – in increasingly complex search spaces. We optimized general steady actuations with EGM and feedback control laws with gMLC. As expected, the optimized feedback control law surpasses the steady actuation control. Intriguinly, the best performance is achieved by a combination of asymmetric steady forcing and phasor control. Moreover, gMLC learns the control law significantly faster than previously employed genetic programming control. gMLC capability to quickly learn feedback control laws directly from the plant has also been demonstrated in experiments, in particular with the successful control of the open cavity, revealing a need of feedback for increased performances. Other experiment successes include drag reduction of a generic truck model under yaw and lift increase of an airfoil under angle of attack at a Reynolds number near one million. Building on thise successes, we belive that gMLC will greatly accelerate the optimization of control laws for MIMO control as compared to GPC.

Deep reinforcement learning for nonlinear closed-loop flow control and sensor placement

R. Paris[1], S. Beneddine[2], and J. Dandois[3],

[1] DAAA, ONERA, Université Paris-Saclay, Meudon, France

Deep reinforcement learning (DRL) provides relevant methods for discovering efficient control laws through interactions with the environment. Unlike most of deep learning application domains (e.g. image analysis or language translation) where gathering training data is relatively cheap, fluid mechanics requires more resources whether it is from numerical simulations or experiments.

Flow solutions also evolve in a (very) high-dimensional space, thus allowing only for partial state observations and forbidding any systematic mapping of the action-state space. These specific constraints highlight the need to both extract relevant information and explore the solution space with highly sample-efficient training methods. Algorithm variants such as the ones using experience replay or curriculum learning arouse a specific interest.

On simple sand-box cases such as a bidimensionnal low Reynolds cylinder flow (refer to fig 1) or a stalled bidimensionnal airfoil flow, DRL demonstrates its ability to derive energy-efficient control policies. The observed robustness of these policies is a direct consequence of the training process that uses a trial-and- error paradigm to optimize the control action.

We also show that the reinforcement learning paradigm is well-suited for seeking sparsity in observations and control actions, a criterion that is crucial in regards to the context. The proposed method leads to a significant reduction in the number of sensors without noticeably degrading control performance. The physical interpretation of these sparsified layout appears to be non-trivial.

Fundings: This work is funded by ONERA and the French Agency for Innovation and Defence (AID) via a PhD scholarship. Their support is gratefully acknowledged.

Machine learning methods for the simulation of turbulent flows in turbomachinery

A. Ferrero[1], F. Larocca[1], A. Iollo[2] and T. Philibert[1]

[1] Politecnico di Torino, Torino, Italy
[2] MEMPHIS Team INRIA Bordeaux Sud-Ouest, Université de Bordeaux, CNRS, IMB, Talence, France

Turbulence modelling represents a critical aspect in the prediction of the flow field in turbomachinery. Recently, high-fidelity simulations like Large Eddy Simulations (LES) or Direct Numerical Simulations (DNS) become possible thanks to the constant increase in computational power that has been achieved in the last decades. However, these simulations remain prohibitive for performance prediction during a design process because of the large number of configurations which must be investigated. For this reason, high fidelity simulations can be exploited to generate trustworthy solutions on representative test cases in order to understand the phenomena which govern the flow field. Furthermore, it is possible to exploit these results to improve the accuracy of low order models which can then be used for design purposes. In particular, Reynolds- averaged Navier-Stokes (RANS) models represent an efficient way to compute the average flow field but they can become quite inaccurate in the presence of separation or transition from laminar to turbulent flow. In this framework, machine learning strategies represent a possible approach to improve the predictive capability of existing RANS models starting from high-fidelity data obtained from LES or experiments [2]. Among the different algorithms, field inversion is a promising strategy. The approach, originally introduced by Paris et al., was exploited to improve RANS models for turbomachinery by Ferrero et al. The method relies on two steps: an optimisation procedure (the field inversion) and a regression performed by machine learning. The first step requires the definition of an optimisation problem where the goal function is represented by the error between the numerical prediction and the reference data: this error is minimised by finding an optimal field of corrections which alter the source term of the turbulence model. The solution of the optimisation problem contains a lot of information: in each point of the computational domain the local correction and all the fluid variables are known. This makes it possible to exploit machine learning algorithms to identify a correlation between some local flow features and the correction field. This regression step allows to generalise the results and to use the data-augmented RANS model for general predictions. Even if the first results of the field inversion strategy seem promising, several open questions remain. First of all, the reference data (experimental or from high-fidelity simulations) are affected by uncertainty and it propagates through the field inversion procedure up to the final data-augmented model. Furthermore, a significant modelling uncertainty is associated to the regression step: the selection of the flow features which should determine the local correction is not trivial. It is possible to follow some basic guidelines (nondimensional inputs, Galilean invariant inputs,...) but it is not clear how to demonstrate that the correlations captured by the regression analysis are based on a cause-effect principle. In this work Artificial Neural Networks and Random Forests are investigated as regression tools to find a correction to the Spalart-Allmaras RANS closure model for the flow in low pressure gas turbines. The correction acts as an intermittency model and allows to extend the original model to transitional low Reynolds number working conditions.

Machine learning-augmented turbulence modeling for RANS simulations of flows over periodic hills

P. Volpiani[1], M. Meyer[1], L. Franceschini[1], J. Dandois[1], F. Renac[1], E. Martin[1], O. Marquet[1], and D. Sipp[1]

[1] ONERA, Meudon, France

Thanks to their low computational cost, Reynolds-Averaged Navier-Stokes (RANS) simulations remain an indispensable tool in the design, analysis, and optimization of many aerodynamic components. Nevertheless, it is well known that complex effects such as flows with separations, high streamline-curvature, strong pressure gradients, etc. are poorly modeled by this approach. With the accelerating developments and the availability of modern machine-learning tools, aerodynamic computations are increasingly influenced by data- science. Therefore, more attention is directed towards data-driven techniques that attempt an improvement of the performance and a generalization of turbulence models. It is a particular focus of such methods to compensate model form errors by training machine-learned model corrections and it is a growing perspective to apply machine learning in the context of turbulence modelling.

We demonstrate a data-driven approach that aims to introduce a correction to the RANS Spalart-Allmaras (SA) turbulence model based on: (i) data assimilation to infer a modelling correction from high-fidelity data, and (ii) machine learning by means of neural network training to construct the correction term as a function of available flow quantities. The final neural-network contribution is a Boussinesq-correction in form of a volume forcing term on the momentum equations, rather than a turbulent eddy-viscosity adjustment. It is well-known that linear eddy viscosity models such as SA suffer from inaccuracies when dealing with massively separated flows. For this reason, flows over periodic hills at distinct Reynolds numbers and geometries were selected to demonstrate the potential gain of machine learning-augmented turbulence models.

Turbulence modeling using CFD-driven symbolic identification

I. Ben Hassan Saïdi[1], P. Cinnella[2], and F. Grasso[3]

[1] Institut Aérotechnique, CNAM, 78210 Saint-Cyr l'Ecole, France
[2] Institut Jean Le Rond d'Alembert, Sorbonne Université, 75005 Paris, France
[3] Laboratoire DynFluid, CNAM, 75013 Paris, France

Computational Fluid Dynamics (CFD) simulations of turbulent flows for industrial applcia-tions largely rely on the Reynolds-Averaged navier-Stokes (RANS) equations supplemented with linear eddy-viscosity models (LEVM) for the Reynolds stresses. RANS models have a much lower computational costs than higher fidelity simulations (LES, DNS) but they are generally inaccurate for non-equilibrium turbulent flows, e.g. flows with separations, streamline curvature or strong pressure gradients.

In the attempt of overcoming the limitations of LEVM, more sophisticated formulations have been proposed in the literature. Among them, Explicit Algebraic Reynolds Stress Models (EARSM) generalize the linear eddy viscosity concept by expressing the Reynolds-stress anisotropy as a function of both the mean strain rate S_{ij} and the rotation rate Ω_{ij} through a nonlinear relationship. The Reynolds-stress anisotropy can then be written as a linear combination of a minimal integrity basis of tensors depending on S_{ij} and Ω_{ij}. The coefficients of the combination are unknown functions of tensors invariants, classically derived from physical considerations.

Recently, many research efforts have addressed the development of flow-specific turbulence models using data-driven methods. Among the possible strategies, a promising approach consists in using machine learning algorithms to learn data-driven corrections to mechanistic constitutive laws for the Reynolds stress tensor based on high fidelity data. The preceding models are trained offline, i.e. outside the CFD models, and are subsequently propagated through a flow solver to compute any other quantity of interest. Such approaches, referred to as CFD-free, deliver data-driven EARSM models customized for a given class of flows, with improved performances not only over the baseline LEVM but also EARSM derived from purely physical arguments. However, due to the offline training, the learned model may cause numerical stiffness once coupled with a mechanical energy. Most importantly, the training necessarily required full-field high-fidelity data for the Reynolds stresses which are not always promptly available.

In this contribution, we present a CFD-driven symbolic identification algorithm extending the work of Schmeltzer et al. Candidate models are embedded with a RANS solver and their fitness is obtained from a CFD solve. The CFD-driven approach is much more flexible with respect to the kind, quality and quantity of high-fidelity data needed for training. Moreover, candidate models preventing the solver to converge can be discarded during the optimization process, leading to numerically robust learned models. To drastically reduce the number of CFD solves during model training and alleviate computational cost, the underlying optimization problem is solved using the CORS (Constrained Optimization using Response Surfaces) algorithm. Results are reported for data-driven corrections of the well-known $k-\omega$ SST model, showing significantly improved accuracy and good generalization capabilities over a class of separated flows.

Wall model for LES based on building-block flows

A. Lozano-Duran[1], and H. Jane Bae[2, 3]

[1] Dept. of Aeronautics and Astronautics, MIT, Cambridge, USA
[2] School of Engineering and Applied Sciences, Harvard University, Cambridge, USA
[3] Gradute Aerospace Lab., CalTech, Pasadena, USA

The prediction of aircraft aerodynamic quantities of interest remains among the most pressing challenges for computational fluid dynamics, and it has been highlighted as a Critical Flow Phenomena in the NASA CFD Vision 2030. The aircraft aerodynamics are inherently turbulent with mean-flow three-dimensionality, often accompanied by laminar-to-turbulent transition, flow separation, secondary flow motions at corners, and shock wave formation, to name a few. However, the most widespread wall models are built upon the assumption of statistically-in-equilibrium wall-bounded turbulence and do not faithfully account for the wide variety of flow conditions described above. This raises the question of how to devise models capable of accounting for such a vast and rich collection of flow physics in a robust and scalable manner.

We propose tackling the wall-modeling challenge by devising the flow as a collection of building blocks, whose information enables the prediction of the stress as the wall. The core assumption of the model is that simple canonical flows (such as turbulent channel flows, boundary layers, pipes, ducts, speed bumps, etc) contain the essential flow physics to devise accurate models. Three types of building block units are used to train the model, namely, turbulent channel flows, turbulent ducts, and turbulent boundary layers with separation. The approach is implemented using two interconnected artificial neural networks: a classifier, which identifies the contribution of each building block in the flow; and a predictor, which estimates the wall stress via non-linear combinations of building-block units. The output of the model is accompanied by the confidence in the prediction. The latter aids the detection of areas where the model underperforms, such as flow regions that are not representative of the building blocks used to train the model. The model is validated in a realistic aircraft geometry from NASA Juncture Flow Experiment, which is representative of external aerodynamic applications with trailing-edge separation.

Acknowledgements A.L.-D. acknowledges the support of NASA under grant No. NNX15AU93A and the MIT Supercloud and Lincoln Laboratory Supercomputing Center for providing HPC resources that have contributed to the research results reported within this work. The authors also acknowledge use of computational resources from the Yellowstone cluster awarded by the National Science Foundation to the CTR.

Developing generalizable data-driven model augmentation using learning and inference assisted by feature-space engineering

V. Srivastava[1], and K. Duraisamy[1]

[1] University of Michigan, USA

This work presents a formalism to improve the predictive accuracy of physical models by learning generaliz- able augmentations from sparse data. Building on recent advances in data-driven turbulence modeling, the present approach, referred to as Learning and Inference assisted by Feature-space Engineering (LIFE), is based on the hypothesis that robustness and generalizability demand a meticulously designed feature space that is informed by the underlying physics, and a carefully constructed features-to-augmentation map. The critical components of this approach are:

1. Identification of relevant physics-informed features in appropriate functional forms to enable significant overlap in feature space for a wide variety of cases to promote generalizability

2. Explicit control over feature space to locally infer the augmentation without affecting other feature space regions, especially when limited data is available

3. Maintaining consistency across the learning and prediction environments to make the augmentation case-agnostic

4. Tightly-coupled inference and learning by constraining the augmentation to be learnable throughout the inference process to avoid significant loss of information (and hence accuracy)

To demonstrate the viability of this approach, it is used in the modeling of bypass transition. The augmenta- tion is developed on skin friction data from two flat plate cases from the ERCOFTAC dataset. The augmented model is then applied to a variety of flat plate cases which are characterized by different freestream turbulence intensities, pressure gradients, and Reynolds numbers. The predictive capability of the augmented model is also tested on single-stage high-pressure-turbine cascade cases, and the model performance is analyzed from the perspective of information contained in the feature space. The results show consistent improvements across these cases, as long as the physical phenomena in question are well-represented in the training.

Machine-learned invariant map for turbulent flow analysis and modeling

K. Fukami[1], and K. Taira[1]

[1] Department of Mechanical and Aerospace Engineering, University of California, Los Angeles, CA 90095, USA

In machine learning, it is difficult to distinguish "seen" and "unseen" fluid flow data. In addition, applications of machine-learning based techniques to "unseen" situations result in dangerous extrapolation. Hence, identifying the borderline of such data sets is important towards practical applications of machine learning to fluid flow analyses and modeling. Furthermore, what may appear as extrapolation in a traditional sense may not be the case due to scale invariance with turbulence. In response, we propose a novel data scaling method for incompressible turbulent flows through sparse regression analysis that reveals the likeliness of data to have been "seen." To analyze the topological similarity among turbulent flow data, we consider the deviation of an invariant map constructed from characteristic equation for the velocity gradient tensor. Axes on the invariant map constructed by fluid flow data are scaled by a non-dimensional scaling factor identified with sparse regression analysis capitalizing on the generalization of the Buckingham Pi theorem . The present method is tested with two and three- dimensional decaying homogeneous isotropic turbulence. We find that the present data-driven scaling is able to identify structural similarities of turbulence beyond the size of scales. The present approach enables the transfer of machine-learned knowledge to support a wide range of fluid flow data analyses by clarifying the process of inter- and extrapolation with data-driven modeling.

List of Participants

L. Agostini	Institut Pprime, France
A. Ahmad	Texas Tech. University, USA
A. Allauzen	LAMSADE, Dauphine Université, France
M. Ancellin	ENS Paris-Scalay, France
H. J. Bae	Harvard, CalTech, USA
M. Beneitez	KTH, Sweden
D. A. Bezgin	TU Munich, Germany
L. Biferale	University of Rome Tor Vergata, Italy
E. M. Bollt	Clarkson Univ., USA
M. Alessandro Bucci	INRIA, France
M. Buzzicotti	University of Rome Tor Vergata, INFN, Italy
D. Capocci	Univeristy of Rome Tor Vergata, Italy
J. Carlier	INRAE, France
D. Caverly	McGill University, Canada
L. Cordier	Institut Pprime, France
G. Y. Cornejo Maceda	LISN, France
F. De Voogt	University of Southampton, UK
N. Deng	IMSIA, ENSTA, France
F. Di Meglio	MINES ParisTech, France
M. Dreisbach	KIT, Germany
Y. Duguet	LISN, France
K. Duraisamy	University of Michigan, USA
M. Elhawary	Institut Pprime, France
T. Faney	IFPEN, France
E. Farzamnik	Uni. Carlos III de Madrid, Spain
D. Fernex	EPFL, IGM, Switzerland
A. Ferrero	Politecnico di Torino, Italy
L. Fery	ENS Lyon, Université Paris-Saclay, France
S. Février	LISN, France
P. Forooghi	Aarhus University, Denmark
J. B. Freund	University of Illinois, USA
K. Fukami	UCLA, USA

A. Giannenas	Imperial College, UK
A. Girayhan Özbay	Imperial College, UK
T. Guegan	ISAE-ENSMA, France
G. Haller	ETHZ, Switzerland
R. A. Heinonen	University of Rome Tor Vergata, Italy
T. Horsin	CNAM, France
X. Jurado	Icube, France
A. Iollo	INRIA, France
T. Kiwitt	RWTH Aachen University, Germany
J. Kou	Universidad Politecnica de Madrid, Spain
A. Kourta	Université d'Orléans, France
T. Kroll	University of Munster, Germany
N. Kumar	Institut Pprime, France
A. Lechevallier	Sorbonne Université, IFPEN, France
S. Lee	KTH, Sweden
Y. Li	Harbin Institute of Tech., China
J.-Ch. Loiseau	Arts & Metiers, France
A. Lozano-Duran	MIT, USA
F. Lusseyran	LISN, France
L. Magri	Imperial College, UK
L. Mathelin	LISN, France
N. Mazellier	Université d'Orléans, France
B. J. McKeon	CalTech, USA
E. Memin	INRIA, France
R. Mochon	Institut Pprime, France
M. Mustermann	Uni. Bochum, Germany
I. Mortazavi	CNAM, France
F. Nataf	France
B. R. Noack	Harbin Institute of Techn., China
D. Papageorgiou	Imperial College, UK
R. Paris	ONERA, France
P.-Y. Passaggia	Université d'Orléans, France
L. R. Pastur	ENSTA, France
T. Philibert	INRIA, France
F. Pino	VKI, Belgium
B. Podvin	LIMSI, France
T. Sapsis	MIT, USA
L. Schena	VKI, Belgium
A. Schreyer	RWTH Aachen University, Germany
R. Semaan	TU Braunschweig, Germany

O. Semeraro	LISN, France
T. Singh	Institute Pprime, France
D. Sipp	ONERA, France
V. Srivastava	University of Michigan, USA
A. Stroh	KIT, Germany
K. Taira	UCLA, USA
P. Thomas	France
G. Tissot	INRIA, France
P. S. Volpiani	ONERA, France
O. Wilk	CNAM, France
J. Yang	KIT, Germany
W. Zhang	Northern Polytech. Univ., China
H. Zolfaghari	University of Cambridge, UK

Useful Information

Talks will be held at the **Amphitheatre Fabry-Perot** of CNAM, indicated with an orange circle on the map next page.

Coffee breaks and lunches will be offered at **Bistrot de la Gaité** situated in front CNAM's main entrance (292 rue St Martin).

Wi-Fi will be available during the conference. CNAM also provides access to an eduroam network.

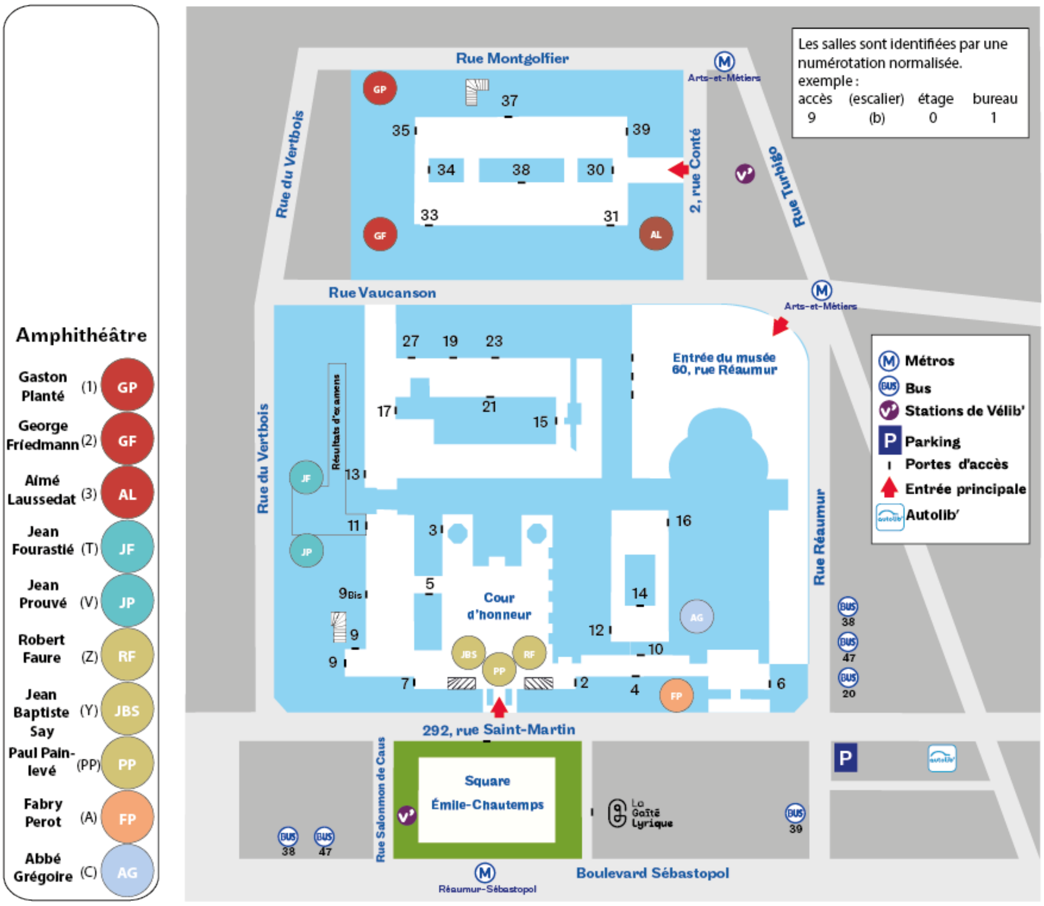
How to get to CNAM?

The **Conservatoire National des Arts et Métiers** (CNAM), founded in 1794 during the French Revolution, is located at 292 rue Saint Martin, in the 3rd arrondissement of Paris, in the historical area of the city named *Le Marais*. It can easily be reached using the Parisian public transportation system, either by bus or metro.

- **Metro:** Arts-et-Métiers (line 3 and 11), Réaumur-Sébastopol (line 3 and 4).

- **Bus:** lines 20, 38 and 47.

A handful of Velib' stations (bicycle sharing system) are also situated around CNAM.


Amphithéâtre
Gaston Planté (1) GP
George Friedmann (2) GF
Aimé Laussedat (3) AL
Jean Fourastié (T) JF
Jean Prouvé (V) JP
Robert Faure (Z) RF
Jean Baptiste Say (Y) JBS
Paul Painlevé (PP) PP
Fabry Perot (A) FP
Abbé Grégoire (C) AG
Les salles sont identifiées par une numérotation normalisée.
exemple :
accès (escalier) étage bureau
9 (b) 0 1
Rue Montgolfier
Arts-et-Métiers
Rue du Vertbois
2, rue Conté
Rue Turbigo
Rue Vaucanson
Entrée du musée
60, rue Réaumur
Résultats d'examens
Cour d'honneur
Rue Réaumur
Métros
Bus
Stations de Vélib'
Parking
Portes d'accès
Entrée principale
Autolib'
292, rue Saint-Martin
Square Émile-Chautemps
Rue Salomon de Caus
La Gaîté Lyrique
Réaumur-Sébastopol
Boulevard Sébastopol

Partner Institutions and Sponsors

This colloquium is part of the European Mechanics Society Colloquia series. It has been funded by the French National Agency for Research (ANR) via the project Flowcon under the grant agreement ANR-17-ASTR-0022 and the European Mechanics Society.

Sponsors