Ph.D. THESIS PROPOSAL:

AI-Driven Control for Wind-Assisted Propulsion

Tutors:
Emmanuel Witrant (UGA/GIPSA-lab) : Emmanuel.Witrant@univ-grenoble-alpes.fr
Janarthanan Rajendran (DU) : Janarthanan.Rajendran@dal.ca

Keywords: distributed systems, machine learning (ML), PDE control, fluid dynamics.

CO_2 emissions from shipping accounted for 2.9% of global emissions caused by human activities in 2018. This major source of pollution is increasing significantly, with a reported year-on-year increase of 4.9% in 2021. In response to these alarming trends, the European Commission has set reduction targets for greenhouse gas emissions from the maritime transport sector as part of a global strategy to reduce emissions from shipping. The use of wind-assisted propulsion (WAP) and sail-assisted cargo ships presents a potential solution for sustainable and efficient shipping, garnering increasing interest from the industrial sector. While the aerodynamics of sails has been extensively studied and optimized for steady-state operation, surprisingly few scientific studies focus on the design of feedback control strategies and the use of distributed sensing capabilities to adapt to changing environmental conditions. Autonomous ship operations are being explored at different levels, ranging from limited autonomous processes and decision-making to fully autonomous vessels. Within this context, the project AutoSail (https://autosail-194045.gricad-pages.univ-grenoble-alpes.fr/) aims to design feedback control methods for sail adaptation based on data from various sensors, with the objective of maximizing the efficiency of WAP.

From physics and ML to grey-box modeling.

Future research on sailing propulsion can leverage a multidisciplinary approach integrating physical modeling, machine learning, grey-box modeling, and experimental validation to enhance predictive accuracy and optimize control strategies. Fostering these research directions, we will offer complementary approaches to improving the accuracy of force predictions, refining sail control, and optimizing WAP systems.

ML presents a powerful approach to optimizing sail performance, predicting aerodynamic forces, and developing real-time adaptive control systems. To address the computational challenges of high-fidelity simulations, we will propose surrogate models trained on CFD-generated data, developed using Gaussian processes or deep neural networks. These models would approximate aerodynamic forces in real time, making fast, adaptive sail control feasible without requiring intensive simulations. Furthermore, given the stochastic nature of wind forces and sea states, Bayesian machine learning techniques could quantify uncertainty in force predictions, leading to more robust and resilient control strategies. Another key area of data-driven ML application is **sensor fusion for real-time sail adjustment**. By integrating data from wind sensors, GPS velocity tracking, and strain gauges on the rigging, ML algorithms can continuously adjust sail trim and orientation to maximize efficiency. We will also develop techniques such as dedicated Kalman filtering and deep learning-based estimators, to enhance state estimation, ensuring optimal sail positioning even under highly dynamic environmental conditions.

(a) Paceship Mouette 19 (6 m)

(b) Dragon Flite 95 (1 m)

(c) MiniJI (3.65 m) financed by this project

Figure 1: Experimental testing environments. Paceship Mouette 19 and Joysway Dragon Flite 95 are already financed and available at Dalhousie University. MiniJI will be instrumented at GIPSA-lab.

A particularly promising direction lies in grey-box modeling, which **integrates first-principles physics with data-driven learning** to balance interpretability and flexibility. While physical models provide the necessary structural understanding of sail dynamics, ML components can refine parameter estimation and adapt the model to real-world variations. This approach is crucial for developing robust control algorithms capable of optimizing sail trim adjustments in real time, ensuring that the driving force is maximized while avoiding flow separation. We will propose new hybrid models that blend RANS simulations with ML-based surrogate models, which will significantly reduce computational costs while maintaining high predictive accuracy.

Experimental validation

To bridge the gap between simulation and real-world sailing, **experimental validation is essential**. Testing different sail shapes (rigid or flexible) and trims under various conditions will allow us to provide informative data sets and help determine the configurations that maximize driving force while minimizing drag. We will carry **full-scale instrumented sailboat trials**, a necessity to evaluate ML-based and model-based control strategies in real-world conditions. Equipping a MiniJI sailboat (see Fig. 1) with force sensors (mast and rigging), flow attachment sensors (ePenons®), pressures on sails and wind measurement (anemometer), and IMU-based motion tracking, we will generate valuable datasets for refining both physics-based and ML-driven models. These trials can assess the real-time performance of adaptive sail control systems and provide direct feedback for improving predictive models. Furthermore, we will equip our MiniJI with **actuated rudder and sail trimming systems**, and perform fully autonomous sailing tests in lake and sea trials. This autonomous platform will provide informative data sets and enable the testing of RL-based and infinite-dimensional control strategies in dynamic environments, helping validate their effectiveness across varying wind and wave conditions. We will also carry additional dedicated experiments on autonomous sailing and on pressure-distribution measurement and jib-trimming control on the DragonFlite 95 and Mouette 19 boats, respectively. These boats, depicted in Fig. 1, are currently available at Dalhousie University and available full time for our project. Such prototypes will serve as testbeds for **developing fully autonomous wind-assisted shipping systems**, contributing to the broader adoption of sustainable propulsion technologies.

By integrating advanced physical modeling, ML, grey-box modeling and rigorous experimental validation, a **more comprehensive approach to optimizing WAP** can be achieved. Improved modeling techniques will enhance force predictions, ML-driven methods will enable real-time adaptability, and experimental testing will ensure real-world applicability. These research directions collectively aim to refine sailing efficiency, reduce reliance on empirical tuning, and pave the way for **autonomous, high-performance sailing and wind-assisted commercial shipping technologies**. By leveraging cutting-edge computational tools and experimental methodologies, significant performance gains in sailing propulsion can be realized, driving forward innovation in both recreational sailing and sustainable maritime transport.

Systems and Control for Fluid-Structure Interaction in sailboats.

We will **integrate AI automation with control-theoretic guarantees to enhance the accuracy, reliability, and adaptability** of AI-driven systems in complex, uncertain environments. A key direction is developing hybrid AI-control approaches, combining RL, deep neural networks, and Lyapunov methods to ensure real-time adaptation and robustness. Another focus is AI-driven control of networked systems, where bio-inspired neural architectures and safe RL frameworks can improve multi-agent coordination, motion planning, and disturbance compensation in dynamic environments like ocean currents and wind variations. Ensuring stability constraints in AI-based learning is crucial for safe, energy-efficient, and adaptive decision-making. By combining ML with formal control guarantees, this research can enable trustworthy, high-performance AI automation in safety-critical applications.

Ultimately, we will evaluate the controllers designed in this thesis on our MiniJI instrumented sailing platform, where **distributed sensing and control strategies can be tested in real-world conditions**. The use of adaptive estimation techniques, such as observer-based PDE controllers, can improve state estimation in the presence of limited sensing, addressing practical constraints in deployment. By unifying boundary control, hybrid switching strategies, and PDE-ODE integration, this research can lead to more autonomous, efficient, and robust WAP systems, significantly advancing the role of wind propulsion in maritime transportation.

Qualifications

- Bachelor and Master's degrees in Mechanical Engineering, Electrical Engineering, or a related field.
- Background knowledge in one or multiple fields: dynamic modeling, machine learning, advanced control, fluid dynamics, robot operating systems (ROS) simulation and implementation.
- Technical writing skills for scientific publications. Communication skills in English.
- A problem-solving-oriented mindset, self-motivation, initiative, resourcefulness, and dependability. Ability to both work independently and as part of a team.
- For international student, a minimum IELTS score of 7.0 or TOEFL iBT score of 92 is required.

How to apply

Interested applicants, please send your CV, copies of transcripts, and previous publications (if any) to Prof. Emmanuel WITRANT (`emmanuel.witrant@univ-grenoble-alpes.fr`) and Prof. Janarthanan RAJENDRAN (`Janarthanan.Rajendran@dal.ca`) using the subject line "PhD Position Application – Automatic Sail - ML".

Other details

All qualified applicants are encouraged to apply. However, only candidates under consideration will be contacted. The starting date is as early as possible.

References

- P. Daoudi, B. Mavkov, B. Robu, C. Prieur, E. Witrant, M. Barlier, and L. Dos Santos. “Improving a Proportional Integral Controller with Reinforcement Learning on a Throttle Valve Benchmark”. In: CCTA 2024 - 8th IEEE Conference on Control Technology and Applications. Aug. 2024.
- A. Rahimi-Kalahroudi, J. Rajendran, I. Momennejad, H. van Seijen, and S. Chandar. “Replay Buffer with Local Forgetting for Adapting to Local Environment Changes in Deep Model-Based Reinforcement Learning”. In: 2nd Conference on Lifelong Learning Agents. Vol. 232. PMLR, Aug. 2023, pp. 21–42.
- S. Smith, E. Witrant, and Y.-J. Pan. “High-Precision Heading Control of an Autonomous Sailboat: a Robust Nonlinear Approach”. In: OCEANS Conference. IEEE. Halifax, Canada, 2024.
- A. Mattioni, S. Zoboli, B. Mavkov, D. Astolfi, V. Andrieu, E. Witrant, P. Frasca, and C. Prieur. “Enhancing deep reinforcement learning with integral action to control tokamak safety factor”. In: Fusion Engineering and Design 196 (2023), p. 114008.