PhD Proposal

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Modeling of propellant sloshing in space vehicle tanks under micro-gravity or low-g maneuver through physics informed machine learning.

Keywords

Propellant sloshing, space tanks, CFD, pendulum models, PINN, GNC simulation, ECSS/SMP

Desired Profile and Skills

- Engineering degree or Master's degree in aerospace or applied data science.
- Skills in fluid mechanics, numerical simulation (CFD), reduced-order modeling methods (mass-spring model, pendulum).
- Interest or experience in physics-informed machine learning (PINN, PIML and SciML).
- Proficiency in C++ and/or Python, familiarity with ECSS/SMP standards is a plus.

PhD Project Description

Physics-Informed Neural Network (PINN) represent a new paradigm in Scientific Machine Learning (SciML), capable of solving both direct and inverse problems for nonlinear Partial Differential Equations (PDEs) [16]. By integrating underlying physical constraints into the architecture of a Feedforward Neural Network (FFNN), PINNs can be trained as surrogate models with little to no labeled data for inferring solutions to PDEs [5]. In the current literature, the implementation of PINN is seen both as a complement and a potential alternative to existing numerical techniques, across a wide range of research fields in science and engineering [13, 2, 3]. Moreover, some frameworks embed Uncertainty Quantification (UQ) by design [17, 18] which make PINN a very interesting candidate for surrogate models in engineering, where robustness of computed solution constitute an important topic.

Context

The behavior of propellants in space launcher tanks directly impacts flight stability, the performance of flight control algorithms, and mission success. During propelled phases, the dynamic effects of sloshing masses can be efficiently modeled using equivalent pendulum models (see for example [10]), but these models become limited when the acceleration regime becomes too weak (and even non-functional in micro-gravity), the sloshing motion too large, or when dominant biphasic behavior occurs.

Problem

In a numerical simulation context, especially for flight control validation and qualification, it is essential to have models that are accurate, fast, and adaptable, capable of representing physical phenomena at different scales and under various flight conditions. The current approaches struggle to provide a generic, fast, and reliable framework for modeling propellant sloshing during all flight phases. CFD provides accurate but costly results, reduced models (pendulums, mass-spring) are effective during powered phases with relatively small sloshing angles (excluding the flip maneuver of the reusable launch vehicle), while PINN offer a promising trade-off between accuracy and cost.

Objectives

This thesis aims to provide reduced models for sloshing in space vehicle tanks in low-g and micro-gravity through PIML since no standard exists.

The main objectives are:

1. Develop a modular C++ software architecture:
   - CFD models (for dataset generation and end to end closed-loop reference simulation),
   - Integration of PINN/PIML models,
   - Interoperability with ECSS/SMP standards and pre-existing pendulum and mass-spring models.
2. Explore, compare, and synthesize sloshing modeling methods:
   - Analytical approach (small angles, linear, pendulum),
   - Numerical CFD simulation (compressible gas and liquid with free surface, evaporation and thermal transport, extraction of wall forces),
   - Physics-Informed Neural Network (PINN), Neural Operator (NO) and Physics-Informed Neural Operator (PINO).
   - Uncertainty and robustness of reduced models through MC-dropout, ensembles, B-PINN, heteroscedatic PINN, or domain decomposition.
3. Propose a model selection strategy based on:
   - Required fidelity level,
   - Simulation constraints,
   - Flight phase and environment.

Methodological Approach

The thesis will rely on a structured approach divided into three main components:

1. Physical and numerical modeling of the fluid mechanics problem, with the aim of defining test cases (low-g maneuver and micro-gravity) and implementing them to generate the datasets for neural network models.

   An incremental approach may be envisioned in order to gradually refine the model with a growing complexity of phenomena to implement:

   - incompressible gas-liquid system with a free surface,
   - gas compressibility and source terms,
   - thermal transport and phase change.

   Special attention will be given to the preparation of the dataset, as the data-driven approach strongly relies on it.

2. Development of full (CFD base on previous modeling) and surrogate (PINN or PIML) models according to ECSS/SMP standards for integration into an industrial environment that ensures good portability across various simulation environments.

3. Performance evaluation on the trade-off between accuracy (with uncertainty quantification) and speed through integration of models into a closed-loop digital simulator and development of recommendations for model selection based on usage.

Proposed Approach

Period	Step
Semester 1	Literature review, construction of test cases, mathematical formulation of the problem
Semester 2	CFD simulations, data extraction, initial PINN prototypes
Semester 3	Development of the modular library, integration of PINN and CFD models
Semester 4	Evaluation, benchmarks, model selection strategy
Semester 5	Integration into a numerical reference simulator to be defined, end-to-end benchmark
Semester 6	Finalization, defense, software submission if applicable

Table 1: Project timeline

Scientific and Industrial Contributions

Accurate and fast evaluation tools for the modeling of propellants in launch vehicle tanks are expected.

In addition, this synthetic approach is expected to provide deeper insights into the limitations and complementarities of analytical models, CFD, and Machine Learning.

Specifically, a direct contribution is expected regarding the modeling of the physical phenomenon:

- A reduced model for sloshing in micro-gravity: where the state of the art does not provide anything usable in an environment coupled with GNC algorithms, unlike phases under acceleration.
- Embeddable sloshing models for flight software: enabling the integration of physically accurate sloshing behavior directly into on-board flight codes for real-time simulation and control.
- Initialization of pendulum models after an orbital phase: where the current state of knowledge forces us to randomly generate the initial state. The goal is to reduce such conservatism.
- Implementation of models during the flip maneuver of reusable launchers: where the dynamics of the launcher may impact sloshing behavior, moving beyond the applicability domain of pendulum models.

A direct contribution to the development of a launcher project, with the ability to simulate complete cases typically simulated via CFD coupling later in the project.

Finally, through integration into an industrial environment, we expect significant operational gains.

Novelty

While PINNs have been successfully applied to terrestrial free-surface flows and generic two-phase fluid benchmarks, no published work addresses propellant tank sloshing in microgravity or low-g launcher maneuvres, including cryogenic compressible two-phase physics and thermal/phase-change effects, with controller-ready surrogates that are ECSS/SMP-compliant. Existing aerospace-related work is either:

- Not physics-informed (deep learning only, less explainable, no V&V robustness)
- Limited to simplified problems (no cryogenics, no spaceflight regimes)

This PhD features a uniquely combination of technique and use case:

- Technique: Advances PINN/PINO for nonlinear, multiphase PDEs capturing onboard propellant physics (Compressible gas–liquid interaction, Free-surface dynamics, Thermal transport and phase change, tank geometry and boundary conditions) and differentiability for Model Predictive Control (MPC).
- Use case: Space launcher tanks in micro-gravity/flip/transition phases where no analytical or reduced models are currently operational.

Maturity

State of the art: PINNs are at TRL 2–3 in fluid mechanics; proven for simpler PINNs, non-cryogenic two-phase flows, and non-aerospace domains.

Gap: No application to aerospace tanks with cryogenic thermodynamics, no integration into industrial simulation environments, no control-loop embedding.

PhD suitability:

- CFD and analytical models for dataset generation are available from ESA/CNES/ONERA.
- PINN/PINO toolchains (PyTorch/TensorFlow, JAX, DeepXDE) are mature enough for immediate prototyping.
- ECSS/SMP interface specifications are public and can be implemented alongside model development.

A 3–4 year research arc allows deepening physics complexity (phase change, boil-off), improving surrogate training stability, and performing closed-loop validation.

Target TRL after PhD: 4–5 — validated in end-to-end simulation with representative hardware/software in the loop, ready for extension to flight-representative testbeds.

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Envisioned Collaborations

ESA, CNES, INRIA, ONERA

Host Laboratory

TBD

Acronyms

B-PINN Bayesian Physics-Informed Neural Network. 2

CFD Computational Fluid Dynamics. 1–5

CNES Centre National d'Études Spatiales. 5, 7

ECSS European Cooperation for Space Standardization. 1–5

ESA European Space Agency. 5, 7

FFNN Feedforward Neural Network. 1

GNC Guidance, Navigation and Control. 1, 4

INRIA Institut National de Recherche en Informatique et en Automatique. 7

ML Machine Learning. 3

MPC Model Predictive Control. 4

NO Neural Operator. 2

ONERA Office National d'Études et de Recherches Aérospatiales. 5, 7

PDEs Partial Differential Equations. 1, 4

PIML Physics-Informed Machine Learning. 1–3

PINN Physics-Informed Neural Network. 1–5

PINO Physics-Informed Neural Operator. 2, 4, 5

SciML Scientific Machine Learning. 1

SMP Simulation Model Portability. 1–5

TRL Technology Readiness Level. 4, 5