



PROGRAMME
DE RECHERCHE
NUMÉRIQUE
POUR L'EXASCALE

Uncertainty Quantification for the closure modeling of the turbulent Reynolds stress tensor

Author : Nassouradine Mahamat^{1,2}

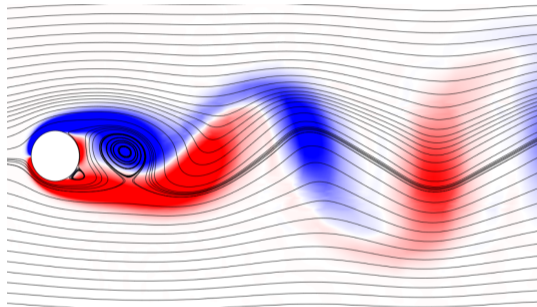
Supervisor : Clément Gauchy¹

PhD Director : Sébastien Da Veiga²

CEA Saclay¹ ENSAI CREST²

Presentation

- Nassouradine Mahamat is a PhD Student in **CEA Saclay** under the supervision of **Clément Gauchy** (CEA Saclay), and is directed by Prof. **Sébastien Da Veiga** at ENSAI CREST.
- Thesis subject : **Uncertainty quantification for the closure modeling of the turbulent Reynolds stress tensor**.
- The PhD program is a part of the **ANR project Exa-MA** (Methods and Algorithms for Exascale) under the France 2030 initiative.
- **Background** : I obtained a Master's degree in Applied Mathematics from the **University of Reims Champagne-Ardenne**, specializing in scientific computing.
- My M2 internship was part of the subject of this PhD program as preliminary work, where I worked on the theme of the **prediction of physical fields under linear constraints** at CEA Saclay



Incompressible Navier-Stokes equations:

$$\begin{aligned}\frac{\partial u_i}{\partial x_i} &= 0 \\ \frac{\partial u_i}{\partial t} + \frac{\partial u_i u_j}{\partial x_j} &= -\frac{\partial p}{\partial x_i} + \frac{1}{Re} \frac{\partial^2 u_i}{\partial x_i^2}\end{aligned}\quad (1)$$

Averaged Navier-Stokes equations (RANS) :

$$\begin{aligned}\frac{\partial \langle u_i \rangle}{\partial x_i} &= 0 \\ \langle u_i \rangle \frac{\partial \langle u_j \rangle}{\partial x_j} &= -\frac{\partial \langle p \rangle}{\partial x_i} + \frac{1}{Re} \frac{\partial^2 \langle u_i \rangle}{\partial x_i^2} - \frac{\partial \langle u'_i u'_j \rangle}{\partial x_j}\end{aligned}\quad (2)$$

The **Reynolds stress tensor** (RST) : $\tau_{ij} = -\langle u'_i u'_j \rangle$ is determined via turbulence **closure modeling** and is **critical** for solving RANS equations.

Goals

In general : Develop an uncertainty quantification framework for the RST modeling

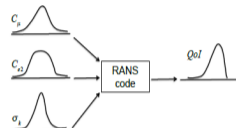
Current objectives : Uncertainty propagation

- Construction of a surrogate model for the Reynolds stress anisotropy tensor \mathbf{b} by Gaussian process regression based on the Pope's model :

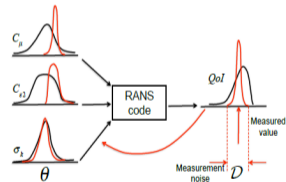
$$\mathbf{b} = \sum_{n=1}^{10} \mathbf{g}^{(n)}(\lambda_1^*, \dots, \lambda_5^*) \mathbf{T}^{*(n)} \quad (3)$$

- Develop a mathematical framework to statistically describe the RST field, by defining risk statistics. In another way, how can the concept of a quantile, defined for a real random variable as an order statistic, be applied to a set of n high-dimensional fields $(\mathbf{b}_1, \dots, \mathbf{b}_n)$?

To model the anisotropic RST field \mathbf{b} , we need to model the strain rate tensor field \mathbf{S} with the physical constraint $\text{Tr}(\mathbf{S}) = 0$. This lead us to solve the following problem.



(a) Uncertainty propagation (forward propagation)



(b) Statistical inference (backward analysis)

Problem statement

In this work, we are considering the multi-output regression task of finding $\mathbf{f} = [\mathbf{f}_1^T, \dots, \mathbf{f}_Q^T]^T : \mathcal{X} \rightarrow \mathbb{R}^P$ such that:

$$\mathbf{y} = \mathbf{f}(\mathbf{x}), \quad \mathbf{y} \text{ is a high dimensional vector, i.e. } P \approx 10^4$$
$$\mathcal{F}[\mathbf{f}(\mathbf{x})] = \sum_{j=1}^Q \alpha^j \mathbf{f}^j(\mathbf{x}) = \mathbf{c}(\mathbf{x}) \quad (4)$$

- **Gaussian process regression**, originally introduced in geostatistics as kriging, is widely used in metamodeling for its probabilistic framework, which captures prediction uncertainty.
- An extension of Gaussian processes (GPR) to multivariate outputs, known as **Multi-output Gaussian Process**¹, has been developed in the literature, with applications in time series and robotics. However, its $O(N^3 + P^3)$ complexity makes optimization expensive when N (data size) or P is large.
- We must reduce the output dimension P to avoid this complexity.

¹ Alvarez, Mauricio A., Lorenzo Rosasco, and Neil D. Lawrence. **Kernels for vector-valued functions: A review**. *Foundations and Trends® in Machine Learning* 4.3 (2012): 195-266

Conclusion

- If you are interested in estimating quantiles of simulated physical fields using HPC, feel free to share with us your interest.
- **Thanks! Any questions ?**