Towards Data Driven Aerodynamic Models: Data Fusion of Experiment and Simulation

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Background & Aims

The study of aerodynamics is crucial for estimating aircraft performance characteristics during the various design phases. Aerodynamic analysis and design rely heavily on three main sources of information; flight testing, wind tunnel testing and computational fluid dynamics (CFD). In wind tunnel experiments, a scaled model is manufactured to collect data about the air flow around the model through measurements. Wind tunnel testing can be expensive and is subject to multiple sources of uncertainty. Aerodynamic data can also be computed with deterministic numerical simulations such as using an incarnation of the Navier–Stokes equations. With the ever-increasing computing power, such numerical simulations have become a must in aerodynamics. However, when dealing with complex configurations and phenomena, particularly near the edge of the flight envelope, numerical simulations tend to lack the required accuracy and come with a significant cost burden.

Research hypothesis: leverage information from the different aerodynamic data sources while controlling the definition and propagation of uncertainty towards the decision-making level.

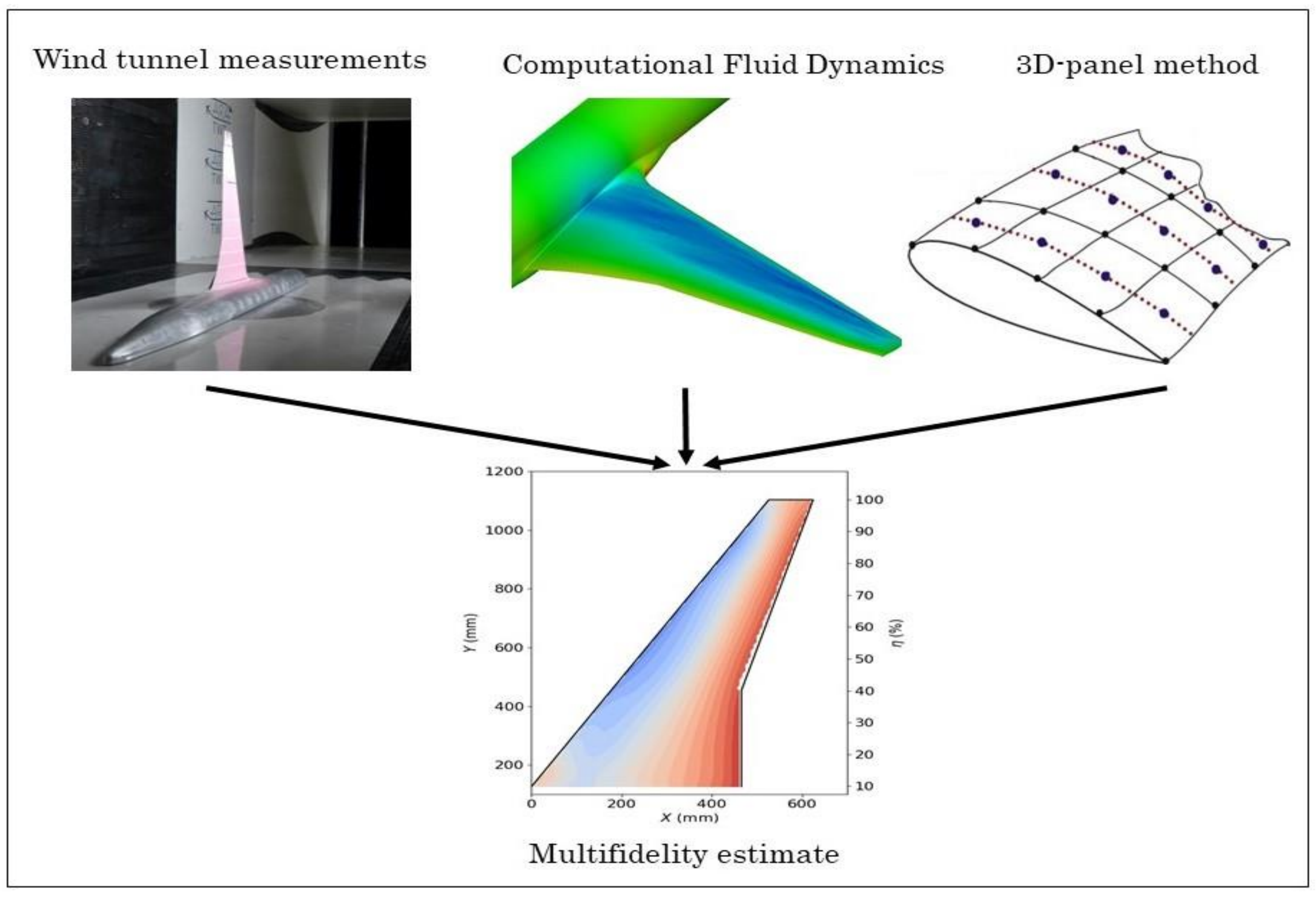

Fig 1: Schematic representation of the multifidelity data fusion.

Method

Multifidelity methodology: Non-hierarchical multifidelity approach based on a combination of Gaussian process surrogate models.

The required amount of data to study the surface flow on a wing implies the use of a 'big data' extension of Gaussian process regression based on stochastic variational inference [3].

Incorporation of expert opinion into fidelity function.

The library adopted in the implementation of the data fusion framework is GPflow, a Python module based on TensorFlow.

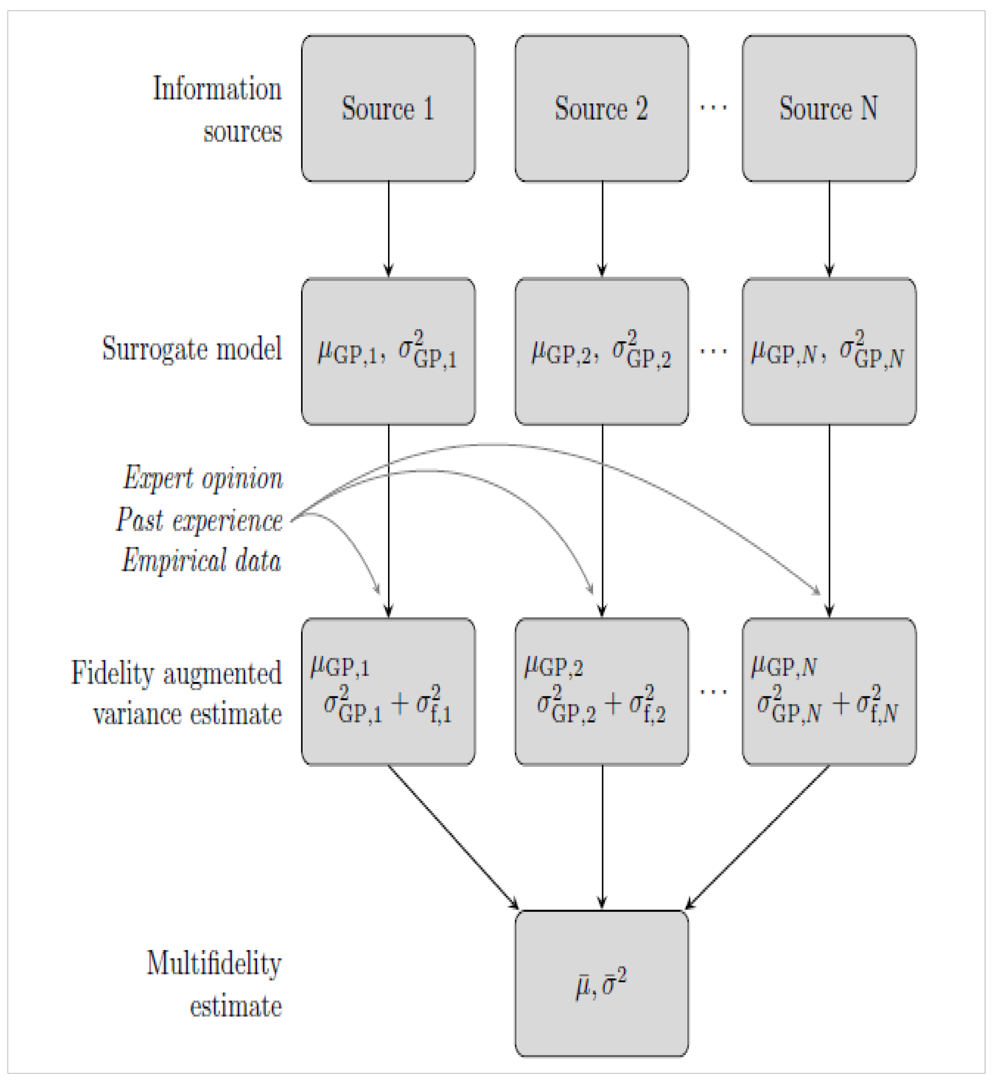

Fig 2: Combination of Gaussian processes with augmented variance. [2]

Results

Application example: Two-dimensional input space of coordinates (X,Y) at M = 0.74 and α = 3° using three information sources [4].

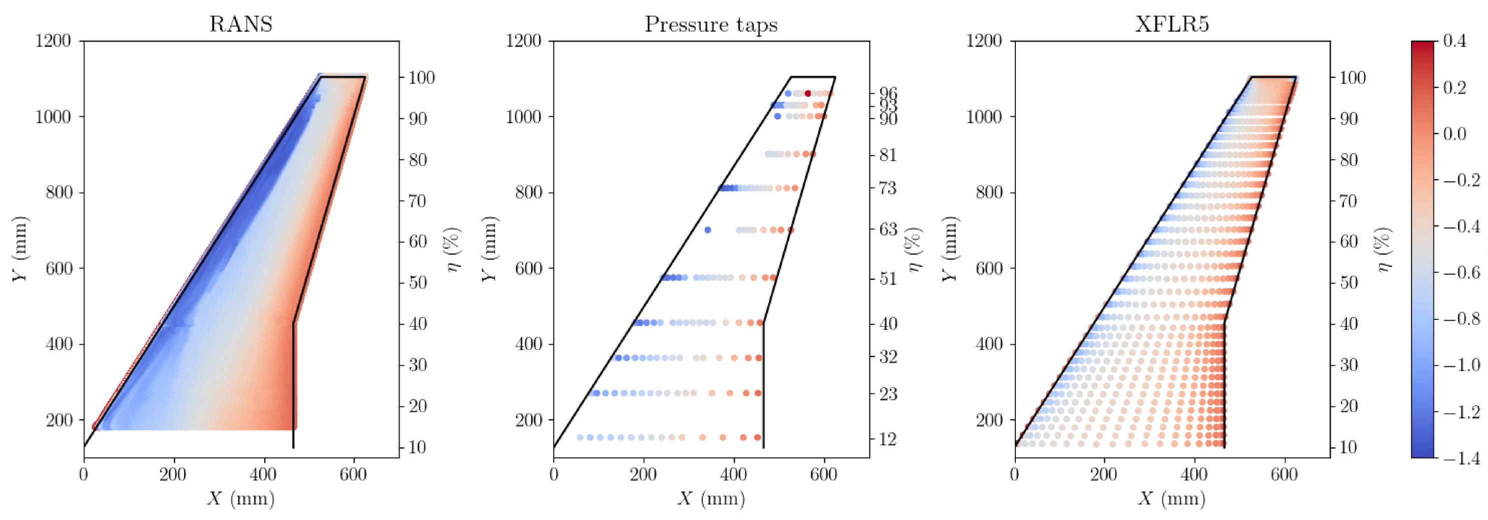

Fig 3: Pressure coefficient of the wing surface.

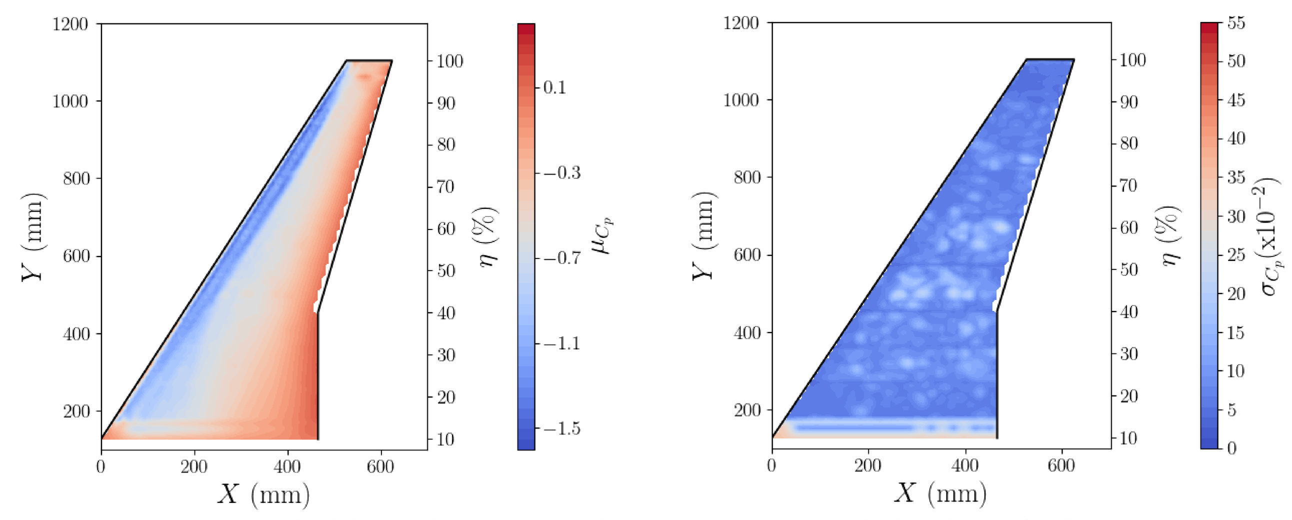

Fig 4: Mean (*left*) and standard deviation (*right*) of multifidelity surrogate model.

Current & Future Work

- **Fidelity function:** Develop a detailed definition of the fidelity function such as taking into account variations in the reliability of an information source under different flow conditions.
- **Gaussian process formulation:** Study the formulation of the Gaussian process with a focus on the covariance function and the hyperparameters tuning.
- **Bayesian Optimisation**: Address the practical question of sensor placement to calibrate the more advanced optical pressure-sensitive-paint technique by applying Bayesian optimisation techniques based on the presented multifidelity surrogate.

Conclusion

This project presents a multifidelity data fusion framework based on a variance-weighted combination of Gaussian process models. Rich exploitation of data describing large aircraft wing pressure distributions obtained from experimental and computational methods has been carried out. The multifidelity data fusion framework has been applied on two- and four-dimensional input spaces using up to four information sources of different fidelity.

References

[1] Rasmussen and Williams (2006), https://doi.org/10.7551/mitpress/3206.003.0001
[2] Feldstein et al. (2020), https://doi.org/10.2514/1.J058388.
[3] Hensman et al. (2013), https://arxiv.org/abs/1309.6835
[4] Anhichem el al. (2022) https://doi.org/10.2514/6.2022-3526

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